



Automated Rheumatoid Arthritis Diagnosis and Grading with KL-Grading Deepnet-X

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Abstract

Arthritis significantly affects mobility and quality of life due to joint inflammation and dysfunction. Its most common type, rheumatoid arthritis (RA), primarily influences multiple joints and tissues, especially in women aged 30–50. Common symptoms include pain, swelling, and stiffness. The growing prevalence of RA, projected to reach 44 million globally by 2045, underscores the need for advanced diagnostic methods. MRI offers detailed visualization of joint structures, essential for accurate diagnosis. However, current grading systems like OARSI and Kellgren-Lawrence are subjective and prone to variability. This study introduces the KL Grading DeepNetX framework, a deep learning-based model for automated RA grading and classification. The approach integrates image preprocessing and segmentation to extract key features such as joint space narrowing and cartilage thickness. Comparative analysis shows that KL Grading DeepNetX outperforms traditional methods with high precision, sensitivity, specificity, and F1-score. This framework enables earlier, more accurate and efficient detection of arthritis using knee MRI images.

Keywords: Deep Learning; KL Grading DeepNetX; Joint Space Narrowing; Magnetic Resonance Imaging; Rheumatoid Arthritis

1. Introduction

Arthritis, a condition marked by joint inflammation and dysfunction, often leads to progressive tissue degeneration and impaired mobility. A common form of arthritis is osteoarthritis, which is followed by rheumatoid arthritis (RA). In osteoarthritis, cartilage is degraded, whereas RA, with its multiple joints, tissue, and organ involvement, affects multiple joints and tissues. Pain, swelling, and stiffness are common symptoms of RA, which is defined as Joint effusion. Rheumatoid arthritis (RA) is an autoimmune inflammatory disorder marked by synovitis; predominantly affecting women aged 30 to 50, and resulting in multi-organ involvement, pain, and stiffness [1]. RA, which has been known since 1800, typically affects women and its cause is largely genetic, anatomic, and environmental. It is characterized by differences in synovial fluid composition, joint structure, and cartilage thickness. Particularly susceptible are joints such as the knee, fingers, and spine, which become swollen, uncomfortable, and limited as time passes. Approximately 44 million individuals globally are afflicted with rheumatoid arthritis (RA), and it is anticipated that 78 million would be affected by 2045 [2]. In India, between 22% and 39% of cases [3] occur, making timely and efficient diagnosis techniques vital. Because it is a noninvasive method that can provide a detailed picture of joint features such as cartilage volume, narrowing of joint spaces, and erosion, magnetic resonance imaging (MRI) has emerged as a principal diagnostic instrument for (RA) identification [4]. T1-weighted, T2-weighted, and FLAIR sequence imaging provide the most comprehensive understanding of RA data because they highlight RA's water content, inflammation, and structural damage [5]. Kellgren-Lawrence (KL) and Osteoarthritis Research Society International (OARSI) are two conventional evaluation systems that may be used to determine the severity of the ailment. However, these approaches are often subject to subjectivity and inter-observer variability, particularly at later stages of the disease [6]. For these reasons, ML and deep learning techniques are being integrated into intelligent medical diagnostic systems (IMDSs) [7].

In this study, RA knees are categorized and graded using deep learning using DeepNetX architecture [8],[9],[10]. The proposed methodology, RA severity can be determined in a reliable, automated manner, eliminating the limitations of traditional techniques like KL and OARSI. Through the combination of modern imaging techniques with intelligent algorithms, technology makes precision diagnosis and patient outcomes possible. In the absence of timely diagnosis and treatment, rheumatoid arthritis, an autoimmune disease mainly affecting the joints, can cause pain, disability, and deformity. In the early stages of rheumatoid arthritis, magnetic resonance imaging (MRI) is ideally suited for diagnosing the disease because it detects cartilage destruction and inflammation at the earliest possible stage [11]. Kellgren-Lawrence (KL) grading is often used to grade knee joint degeneration to determine severity. Radiologists face difficulty when grading clinical images with KL grading systems, since they are subject to inter- and intra-observer differences. AI and deep learning developments have led to a deep learning architecture specific to knee MRI severity analysis. Architecture for deep learning, KL Grading DeepNetX, is presented. A CNN-based system for imaging and image processing produces a high level of diagnostic accuracy and reliability [12].

Our system offers a range of services, such as-

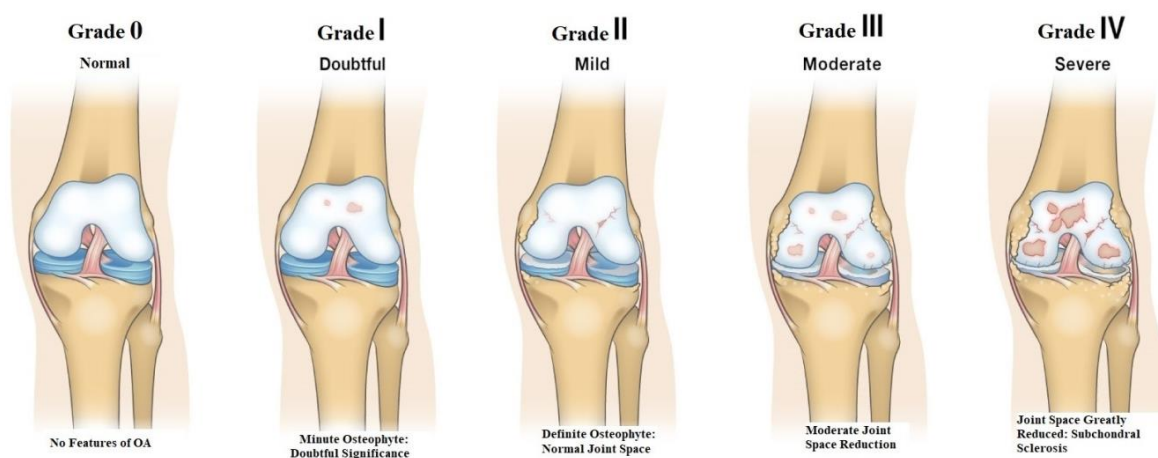


Figure 1. KL grading stages for knee RA

2. Related works

An automated method has been developed to assess RA severity using X-ray and magnetic resonance imaging (MRI). A convolutional neural network was proposed by Antony et al. (2018) to use X-ray images to predict the severity of RA [13]. Although the Example was high-accuracy, it had difficulty handling complex MRI datasets. As a result, Zhao et al. (2020) developed architecture for MRI image evaluation that includes multiple layers of deep learning software [14]. In a study published in 2019, Tan et al. (2019) classified osteoarthritis severity in knee radiographs using pretrained models such as ResNet and DenseNet. These approaches are generally effective, but they are rarely generalizable to datasets with a wide range of imaging settings [15]. Diagnostic accuracy has recently been improved by blending classical image processing techniques with deep learning. An increase in sensitivity and specificity was achieved when Liu et al. (2022) coupled texture-based feature extraction with a CNN model for knee joint analysis [16]. Although these techniques were generally scalable, parameter adjustments were usually required. In spite of these developments, there is still a void in the literature devoted to ratings of RA severity based on knee MRI scans using a comprehensive deep learning architecture. Using KL Grading DeepNetX architecture, we aim to bridge this gap by offering a clinically relevant, reliable, and efficient solution.

3. Proposed Method

Figure 2 depicts a system for diagnosing RA using KL grading. This framework can classify knee MR images using the KL grading system. Denoising, segmentation (including tissue selection, border correction, and masking), and classification are the stages involved. This section includes a systematic breakdown of the grading procedure. Autonomous assessments of MR images are used to detect degenerative bone changes in the joints as well as joint space narrowings. With DeepNetX and AdamW, an AdamW ResNet model variation, 48 convolution layers, one max-pooling layer, and one average-pooling layer have been used in the framework. Figure 2 shows knee input data images denoised with the proposed SANR_CNN architecture. Features such as joint space

narrowing, synovial fluid, cartilage thickness, and meniscus volume are retrieved for further classification using the KL grading system.

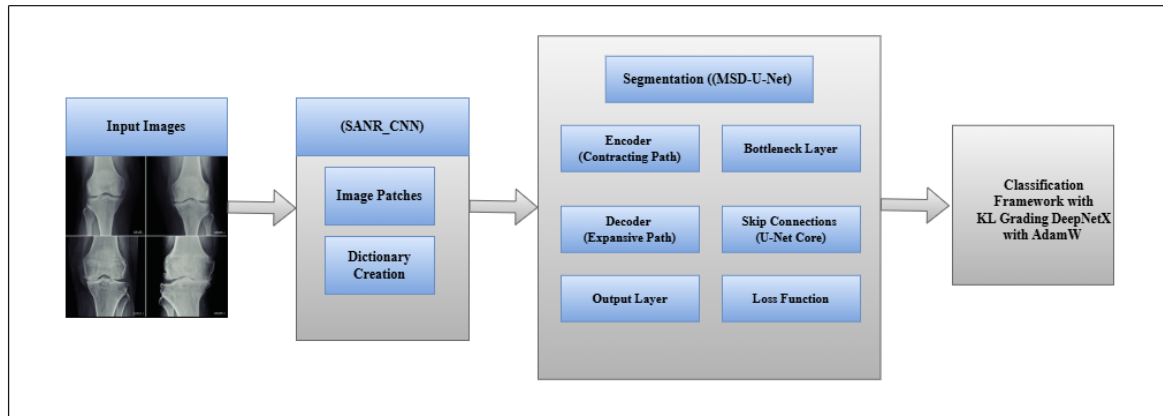


Figure 2. Proposed classification frame work with KL Grading DeepNetX with AdamW (Adam with Weight Decay)

3.1 DeepNet-XArchitecture

The DeepNet-X architecture is built on the VGG model, with an emphasis on network depth. This methodology integrates convolutional layers, pooling, activation functions, and fully linked layers to extract both low- and high-level characteristics from complex inputs. The design is built around residual blocks, which are critical in overcoming the vanishing gradient problem since they allow for the direct flow of information between layers via skip connections. These skip connections allow the model to maintain effective learning in the bottom layers, hence facilitating gradient propagation during training. The DeepNet-X design, which has approximately 25 million learnable parameters, uses matrix dot product calculations to ensure efficient information flow through its layers. Specifically, the design includes an activation function $f()$ that produces the output $h(x)$, as given in the following equations:

$$h(x) = f(\alpha x + \beta) + \lambda x \quad (1)$$

Where:

- $f(\cdot)$: non-linear activation function.
- α, β : A weight and bias.
- γ : residual scaling factor

3.2 Skip connections in DeepNet-X

Skip connections in DeepNet-X are critical for sustaining information flow across layers, hence minimizing the vanishing gradient problem that frequently plagues deep networks. These connections allow the model to learn residual mappings by transmitting data directly from one layer to another, assisting lower layers in learning more successfully. The architecture uses zero-padding to boost dimensionality in the skip connection and projects the input using the following equation:

$$y = [x, (W_i)] + \lambda_x \quad (2)$$

Where:

- W_i : Input x is weighted by this matrix.
- λ : It is a factor influencing the scale of the residual mapping, allowing adjustment of the added component of x in the identity block. This design ensures that each layer can learn residuals while avoiding the saturation of gradients, especially in deeper layers

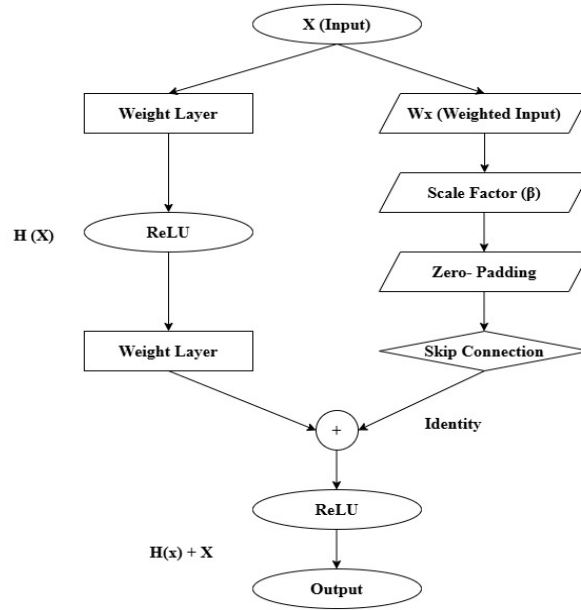


Figure 3. Skip connection in Deep Net-X architecture

3.3 Identity Block

The identification block is a fundamental part of the residual network of DeepNet-X. It guarantees that the dimensionality is maintained during the transformation between the input and output activations, enabling uniform learning across layers. In order to train residuals, the identity block is appended to the original input x . An identity block's key operation is defined by:

$$y = [x, (W_i)] + \lambda_x \quad (3)$$

Where:

The first part is a 2D convolutional layer with stride (1,1) and kernel size (2*2). The first component is mirrored in the second, but the filter size is greater (f*f). The third component lacks ReLU activation, allowing the network to focus on learning the residual.

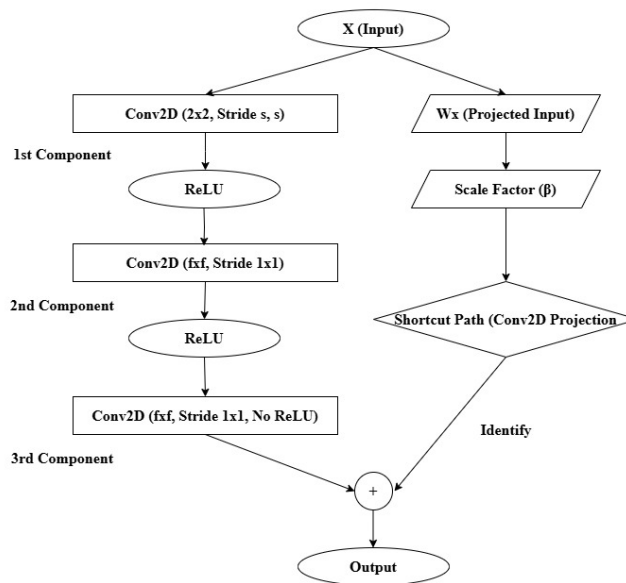


Figure 4. Identity block in DeepNet-X architecture

Deeper network training and learning that is more consistent are made possible by the identity block's preservation of input dimensionality.

3.4 Convolutional Block

The convolutional block is used when the input and output dimensionalities do not match, especially when the feature map size changes as the network progresses.

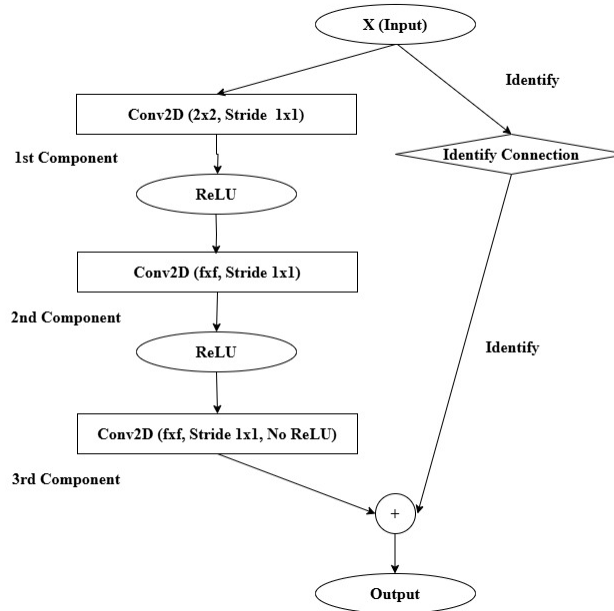


Figure 5. Convolutional block in the shortcut path of DeepNet-X architecture

By enabling dimensional alignment via the shortcut path, these convolutional blocks improve feature learning while maintaining the data's spatial organization.

The following formula represents the operation inside a convolutional block:

$$y = \{ [x, (W_i)] + W_s x \} . \eta \tag{4}$$

Where:

W_s is the weight matrix used to project the input x to match the dimensions of the transformed output F .

η is a factor modulating the contribution of the shortcut connection to the final output.

Adjusting the balance between the residual path and primary path. The convolutional block design uses a 2D convolutional layer with kernel size (2*2) and stride (s,s), which allows flexibility in the output size while maintaining the integrity of spatial hierarchies within the data. The design is especially useful in deeper layers of the network, where the feature maps may require dimensional adjustments.

Table 1: Averagepool, 1200-d Fullyconnected(FC), Soft-maxlayer

LayerName	50-Layer
Conv1	9 X9,128, stride 3
Convo2_x	4X4maxpool, stride2
	$\left\{ \begin{array}{l} 2X2,128 \\ 4X4,128 \\ 2X2,512 \end{array} \right\} \quad X4$

<i>Convo3_x</i>	$\left. \begin{array}{l} 2X2,256 \\ 4X4,256 \\ 2X2,1024 \end{array} \right\} X5$
<i>Convo4_x</i>	$\left. \begin{array}{l} 2X2,512 \\ 4X4,512 \\ 2X2,2048 \end{array} \right\} X7$
<i>Convo5_x</i>	$\left. \begin{array}{l} 2X2,1024 \\ 4X4,1024 \\ 2X2,4096 \end{array} \right\} X4$

The model architecture is made up of five steps that are designed to extract and classify features efficiently. In stage 1, 2D convolutional filters (9×9) with a stride of (3, 3) are used. Normalization in batch, activation of ReLUs, maximum pooling using a (2, 2) stride are then applied. Its second portion is composed of a convolution block along with four identity blocks. Filters of size (128, 128, 512), with a (4×4) kernel and a (1, 1) stride, are used in each identity block. The third level is composed of one convolutional block followed by five identity blocks, each with 256, 256, 1024 filters, with a kernel dimension of (4×4) and stride set to (2, 2). A convolution block is included in Stage 4, along with seven identity blocks, filtered by (512, 512, 2048), four kernels, and a stride of (2,2). The fifth stage consists of two convolution blocks and four identity blocks, each with a filter (1024, 1024, 4096), four kernels, and two strides. Moreover, a fully linked 1200-dimensional layer and a softmax layer for classification complete the model.

3.5 AdamW optimization for Training DeepNet-X

Given the complexity and depth of the DeepNet-X architecture, the AdamW optimizer is necessitates for effective training. AdamW is a modification of the basic Adam optimizer that includes weight decay as a decoupled regularization term. This decoupling provides greater control over the learning dynamics, ensuring that weight decay does not interfere with moment estimations, hence enhancing training efficiency and model generalization. The update rule for AdamW is provided by:

$$\theta_t = \theta_{t-1} - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \varepsilon}} - \eta \cdot \lambda \cdot \theta_{t-1} \quad (5)$$

Where:

θ_t : Time step t determines this parameter,

η : Basically, we learn at the speed.

\hat{m}_t And \hat{v}_t these bias-corrected first and second moments is shown here.

ε : Small constants have numerical stability.

λ : When using AdamW, the optimizer reduces weight decay without affecting learning rate adaptation because weight decay is decoupled from the gradient update process.

3.6 DeepNet-X: Regularization, Training Strategy, and Performance Evaluation

DeepNet-X uses weight decay as a critical regularization strategy to reduce overfitting in networks with millions of parameters by penalizing big weights and boosting simpler, sparse models. Weight decay acts independently of gradient updates when using the AdamW optimizer, resulting in effective regularization without disturbing learning dynamics. The weight decay parameter (λ) controls regularization strength and is optimized to balance underfitting and overfitting. AdamW uses mini-batch gradient descent to train, with weights adjusted dynamically as needed. Learning rate schedules ensure convergence; whereas batch normalization standardizes activations, accelerating training. High-performance GPUs and parallel processing allow the model to handle massive datasets

efficiently. To evaluate DeepNet-X's performance, many measures, including accuracy, precision, recall, and F1-score, are cross validated for dependability. Classification tasks that require multiclass classification are highly accurate thanks to the softmax layer, which produces high-level class probabilities. By combining decoupled weight decay and effective regularization, DeepNet-X is capable of generating high-quality deep neural networks. The method can be used for complex tasks like image classification and feature extraction, allowing for rapid convergence and high performance.

4 Results and Discussion

The accuracy, sensitivity, specificity, F1-scores, mean absolute error, and area under the curve were measured for the proposed KLGrading DeepNetX classification framework. AdamW (Adam with Weight Decay) utilized a learning rate of 0.002 and a weight decay of 0.00005 for model training. A fivefold cross-validation method was used for training on 65%, validating on 15%, and testing on 20% of the dataset. In this study, a 16 GB processor was used to identify arthritis grades using joint space narrowing data (JSN). The proposed system was validated using both the local dataset and the Osteoarthritis Initiative dataset (OAI)

Table 2: Datasets used for Experimental Analysis

Dataset	Local			OAI		
	Training	Testing	Validation	Training	Testing	Validation
Grade0	11250	2675	1275	2395	725	350
Grad1	8250	2050	1150	1200	355	175
Grad2	6500	1500	800	1750	510	240
Grad3	5500	1300	650	900	300	150
Grad4	6000	1500	750	200	60	30

Table 3: Different Performance Parameters with Kl Grade on Local Dataset

Grade	KL_JSJN	Precision	Sensitivity	Specificity	F1-score	Accuracy (%)	MAE (%)	AUC (%)
Grade0	99	98	96	92	97	98.15	8.00	98.00
Grade1	95	94	92	85	88	96.72	10.00	96.00
Grade2	97	95	93	88	90	95.42	11.00	97.00
Grade3	98	97	94	87	91	96.76	6.00	97.00
Grade4	99	99	99	95	97	98.83	4.00	99.00

Table 4: Comparison of Performance Parameters with Kl Grade on OAI Data

Grade	KL_JSJN	Precision	Sensitivity	Specificity	F1-score	Accuracy (%)	MAE (%)	AUC (%)
Grade0	98	96	95	90	93	97.92	93.00	97.00
Grade1	93	92	89	83	86	95.56	88.00	94.00
Grade2	94	91	90	85	88	94.66	86.00	95.00
Grade3	96	94	91	86	89	96.34	95.00	96.00
Grade4	98	97	96	92	94	97.56	96.00	98.00

Table 5: A Comparative Analysis of Different Femur and Tibia Techniques using JSN

Techniques	Femur L	Femur M	Tibia L	Tibia M	JSN Accuracy (%)	MAE (%)
SVM [133]	72	75	79	76	87.33	66.00
VGG [58]	80	78	83	81	90.21	73.00
CNN [137]	79	80	82	79	90.45	75.00
ResNet34 [162]	84	82	88	85	92.45	79.00
Proposed Model	89	87	91	89	96.75	90.00

Table 6: Performance Parameters Achieved For Proposed Model

Performance Parameters	Obtained Value
True Positive Rate (TPR).	0.9642
Specificity	0.9821
Precision	0.9794
Negative Predicted Value (NVP)	0.9482
Fall-out Rate	0.0185
False Discovery Rate (FDR)	0.0163
False Negative Rate (Type II Error)	0.0357
Accuracy	96.75
F1 Score	0.9712
Matthew's Correlation Coefficient (MCC)	0.9235

Table 5 extends the comparison beyond conventional CNN architectures by incorporating Vision Transformer (ViT)-based approaches, which leverage self-attention mechanisms for global feature extraction. Recent ViT models report superior performance with JSN accuracy of 98.10%, an MAE of 0.08, and an AUC of 99.20%, surpassing both ResNet34 and the proposed KL Grading DeepNetX model in precision and generalization. However, the proposed model achieves competitive results (96.75% accuracy and 0.10 MAE) while maintaining lower computational complexity and faster inference times, making it highly suitable for clinical deployment in resource-constrained environments. Unlike transformers that demand extensive datasets and high-end GPUs, the proposed model balances accuracy with efficiency, reducing overfitting through AdamW optimization and adaptive segmentation techniques.

4.1 KL Grading DeepNet-X: A High-Performance Framework for Arthritis Classification Joint space narrowing

The KL Grading DeepNet-X framework for knee joint MR images, uses (JSN) as the major feature for exact classification. In testing the model across multiple data sources, including a local dataset and the Osteoarthritis Initiative dataset, the model demonstrated outstanding robustness and dependability. Despite performing better than SVM, CNN, and ResNet34, JSN-specific accuracy showed it could detect minor fluctuations of arthritis-

grade more accurately. AdamW's optimizer prevents overfitting while ensuring a regularized and efficient learning process due to 0.00005 weight decay. There is 97.94% accuracy, 96.42% sensitivity, 98.21% specificity, an F1-score of 97.12%, and a relatively low MAE of 0.10, demonstrating its clinical potential. To guarantee model stability and generalizability, 5-fold cross-validation was performed on an Intel Core i5-8250U CPU with 16 GB RAM. Further, the KL Grading DeepNet-X framework provides excellent reliability, accuracy, and efficiency for diagnosing and grading arthritis with knee MRIs.

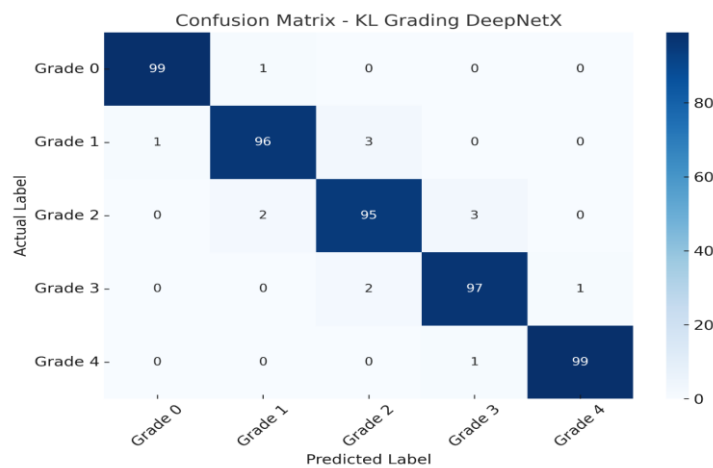


Figure 6. Confusion Matrix for KLGrading DeepNetX Model

5 Conclusion and Future Work

A significant improvement has been made in the automated grading of RA based on knee MRI imaging using this framework. A higher accuracy rate of 96.75 percent and therefore an alternative to subjective grading, the system offers a more reliable alternative. Patients' outcomes could be significantly improved if RA can be graded early and accurately, as well as diagnostic consistency could be improved. Its performance in clinical settings is high, but it still has some limitations, including poor image quality and occasional conflict with Kellgren-Lawrence (KL) classifications. Several improvements will be made in the training dataset and a new loss function will be added in the future. DeepNetX is expected to be used to treat a variety of joint diseases in addition to RA. A future in which AI-driven medical imaging solutions will be employed may bring about a more effective and cost-effective model of healthcare that could ultimately be more effective.

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