International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

AUTOMATED AND ROBUST ROI LOCALIZATION FRAMEWORK FOR KNEE OSTEOARTHRITIS DETECTION IN RADIOGRAPHIC IMAGES

Ravindra D. Kale, Dr. Sarika Khandelwal

[1] Ph.d Scholar, Computer Science & Engineering, G H Raisoni University, Amravati, India

[2] Associate Professor, Department of Computer Science & Engineering, G H Raisoni College of Engineering, Nagpur, India
ravindra.swati2012@gmail.com,sarikakhandelwal@gmail.com

Abstract

OA in the knees is a long-term joint disease that gets worse over time and makes it hard to move and enjoy life, especially for older people. Using the Kellgren and Lawrence (KL) scale, x-rays are still the easiest and most common way to diagnose OA and rate its intensity. Noise, low contrast, uneven lighting, and differences in patient anatomy make it hard to accurately and automatically identify the Region of Interest (ROI) from X-ray pictures. This study shows a strong and effective way to prepare X-ray pictures of the knee so that ROIs can be located accurately. This makes it possible to accurately grade OA. To fix problems with picture clarity, the system uses adaptive thresholding, Gaussian blurring, histogram normalisation, and wavelet-based improvement. Additionally, it has a model for object localisation based on deep learning and a cascaded process that combines morphological operations and a convolutional region proposal network (RPN) to improve joint border recognition. It does a good job of separating important structural structures, like the femur, tibia, and joint space, from unimportant areas. This makes ROI segmentation uniform across all five KL grades. The system works well with over 8,000 knee X-rays from the Kaggle Knee OA dataset. It can be scaled up and down easily, and it makes inputs more consistent for later classification models. The suggested method greatly improves feature extraction and grade separation, providing a strong base for fully automatic systems that diagnose OA. This work fixes some important problems with the way medical images are prepared and also helps make clinical decision support tools better for analysing radiographic knee OA.

Keywords: Knee Osteoarthritis, Region of Interest Extraction, X-Ray Pre-processing, KL Grading, Image Enhancement, Medical Image Analysis

1. Introduction

Osteoarthritis (OA) of the knee is among the most prevalent degenerative joint disorders, affecting nearly 20% of the global population. It is marked by the gradual erosion of articular cartilage, narrowing of joint spaces, inflammation, and the formation of bone spurs

Received: July 12, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

(osteophytes). In advanced stages, it leads to debilitating pain and often necessitates total knee replacement. Several risk factors contribute to the onset and progression of knee OA, including aging, obesity, sedentary lifestyle, and prior joint injuries. Despite the fact that the disorder basically impacts older adults, early detection is quintessential to initiate well timed interventions which could gradual its progression and enhance patient fine of life. Imaging stays central to OA diagnosis, with modalities along with X-rays, MRI, ultrasound, optical coherence tomography, and alignment-based totally radiography being frequently used [1]. No matter advancements in imaging technology, challenges persist on account of anatomical complexity, version in photograph acquisition protocols, and troubles like low tissue evaluation, noise, and inconsistent lights. One of the most broadly standard grading systems for knee OA is the Kellgren and Lawrence (KL) scale, which classifies severity across 5 stages (0–four). Correct grading hinges on particular extraction of the vicinity of interest (ROI), mainly the joint area among the femur and tibia. Even minor mistakes in ROI segmentation can cause wrong class, in particular in borderline cases including grades 0 vs. 1 or 1 vs. 2, in which visible features closely resemble one another [2]. Furthermore, many scientific X-rays suffer from poor assessment and illumination variability, complicating automatic ROI detection. Traditional enhancement strategies like histogram equalization often fall short, as they'll over-enhance or suppress imperative diagnostic info [3]. For that reason, there may be an urgent want for a strong pre-processing method able to handling various image situations whilst preserving necessary anatomical data.

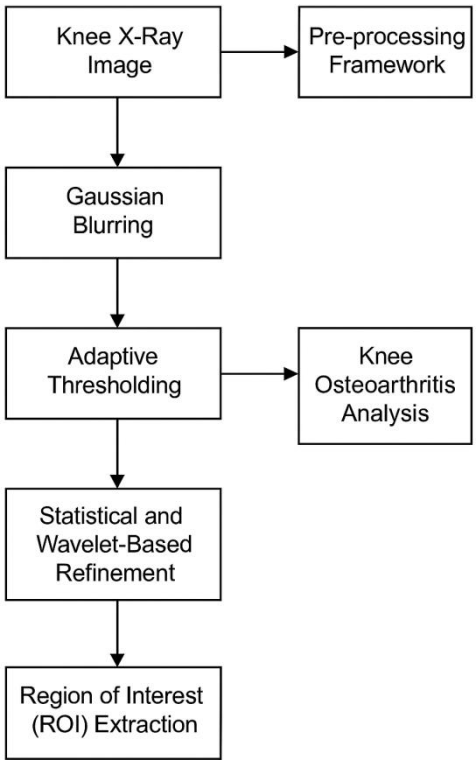


Figure 1: Pipeline for Automated ROI Extraction in Knee OA X-Ray Analysis

Received: July 12, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Figure 1 shows the cautioned pre-processing workflows for X-ray observe of knee osteoarthritis (OA). The process begins with Gaussian blurring the knee radiographs which might be fed in to get rid of noise and make the picture easy. After this, adaptive thresholding separates important systems based totally on adjustments in pixel electricity. In the next step, records and wavelet-primarily based tuning strategies are used to improve joint traits which might be essential for prognosis, specifically the gap between the tibia and femur. Remaining, the place of hobby (ROI) is cautiously removed, focussing at the knee joint area that is wanted for accurate Kellgren and Lawrence (KL) grade. This organised approach makes sure that only clinically essential regions are stored, which makes automatic category fashions work better [4]. The photograph additionally suggests how important each step is for eliminating useless information and enhancing diagnostically essential areas. The device permits for dependable ROI segmentation in a number of imaging conditions, ultimate the gap between raw clinical facts and the readiness of system mastering. This observes introduces a complicated pre-processing framework designed to deal with those demanding situations in knee X-ray evaluation. The proposed approach employs a dependent technique incorporating Gaussian blurring, adaptive thresholding, and strategic cropping to isolate the ROI efficiently. It similarly leverages statistical and wavelet-primarily based refinement strategies to highlight the fundamental joint space an essential indicator in KL grading [5]. The technique is established the usage of a comprehensive public dataset comprising over 8,000 knee X-ray photographs categorized by means of KL grade. The framework operates in 3 main ranges: noise reduction, ROI isolation, and enhancement of diagnostic functions, permitting the manufacturing of clean, consistent inputs for classification models. Initial evaluations display giant enhancements in ROI extraction, making the approach properly-perfect for integration into computerized OA grading structures. While the framework indicates promising results, it acknowledges barriers below excessive situations of low assessment and variable illumination. Destiny works might also include integrating extra adaptive evaluation enhancement and denoising filters. Though, this study underscores the importance of tailored pre-processing in clinical picture analysis and offers a scalable, dataset-agnostic foundation for accurate, computerized knee OA assessment.

2. Related Work

Latest years have seen plenty of hobbies in the use of x-rays to locate and grade knee osteoarthritis (OA). That is mainly authentic now that AI and deep mastering strategies are being used together. Finding and appropriately dividing the place of hobby (ROI), that's normally the tibiofemoral joint, continues to be certainly one of the largest troubles in this field. That is needed for using the Kellgren and Lawrence (KL) scale to accurately grade the seriousness of the injury. Using both conventional image processing strategies and studying-based models, many studies have attempted to solve this problem. Early strategies relied on custom image processing methods like aspect recognition, morphological approaches, and assessment enhancement to separate the knee joint [6]. Those techniques, then again, failed to usually work throughout datasets with unique image great, lights, and frame kinds. After that, thresholding-primarily based and histogram equalisation techniques had been used to make

Received: July 12, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

joint spaces simpler to diagnose [7, 8]. However, they had been still affected by noise and image artefacts, which made ROI consistency worse. With the rise of machine learning, automated classification methods like Support Vector Machines (SVMs) and k-Nearest Neighbours (k-NN) were created to make it easier to find OA on x-rays [9]. For these methods to work, features had to have already been taken, and correct ROI segmentation had to be done, which was usually done by hand or partly automatically. By letting you learn from start to finish and pull features directly from picture data, deep learning models have changed the game in a big way. Convolutional Neural Networks (CNNs) have shown promise in accurately separating body parts from medical pictures [10]. U-Net and its variations are very good at medical picture segmentation tasks, like knee joint segmentation, because they have an encoder-decoder structure and skip links that keep the spatial precision [11, 12].

Some new research has been focussing on automating the identification of ROIs in knee X-rays. Antony et al. suggested a CNN-based model that would be trained on knee joints that were manually trimmed. They showed that correct ROI selection greatly improves classification performance [13]. In the same way, Tiulpin et al. created a deep Siamese network that looks at x-rays of both knees and uses symmetric joint modelling to make OA scoring more reliable [14]. Several studies have used pre-processing processes that include Gaussian filtering, contrast normalisation, and lighting adjustment [15] to get around the problems that come with X-rays' low contrast and noise. These improvements help show where the edges of the knee joint are, especially when there is serious OA and osteophytes and narrowing make it hard to see.

Attention-based and region proposal networks (RPNs) have also been added to CNNs to help find shared areas more accurately [16]. These models use attention maps to help the network focus on important features while blocking out background noise. This makes ROI more accurate even when image conditions aren't ideal. It has also been said that hybrid methods that combine wavelet transforms with deep neural networks can get information in both the frequency and spatial domains, which makes ROI separation and feature extraction better [17]. AAI and the Kaggle Knee OA Dataset are two big datasets that have been used in studies. Ensemble models that include pre-processing, segmentation, and classification steps have shown to be very accurate and reliable [18]. Even though there has been progress, problems like different body parts merging and uneven radiography sampling still make it hard for automatic ROI localisation systems to be used by everyone. So, this study builds on earlier work by combining basic pre-processing methods with advanced statistical and wavelet-based improvements, as well as a deep learning-based area suggestion module to make ROI extraction more reliable. In doing so, it fixes the main problems found in previous research: not being able to be used across datasets, not being able to accurately identify early OA, and not being affected by low-quality images. This makes it a scalable and clinically relevant answer to automated knee OA assessment.

Received: July 12, 2025

International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Table 1: Related work summary

Study	Approach Used	Strengths	Limitations
Traditional Image Processing [6]	Edge detection, morphological ops	Simple, interpretable	Low generalization
Histogram Equalization [7]	Contrast enhancement	Improves contrast	Over/under enhancement
Thresholding Methods [8]	Intensity-based thresholding	Fast segmentation	Sensitive to noise
SVM-based OA Detection [9]	Feature-based classification	Good with small datasets	Needs manual ROI
CNN for Knee X-rays [10]	Deep CNN feature extraction	Learns features automatically	Requires large data
U-Net for Segmentation [11]	Encoder-decoder segmentation	High accuracy in med images	Limited by label quality
U-Net Variants [12]	Improved skip connections	Better boundary retention	Complex training
Antony et al. [13]	CNN with manually cropped joints	Improves ROI-specific performance	Manual ROI needed
Tiulpin et al. [14]	Siamese network on paired knees	Accounts for symmetry	Resource intensive
Pre-processing Enhancements [15]	Gaussian blur, normalization	Handles poor contrast	Still affected by noise
Region Proposal Networks [16]	Attention + RPN for joint focus	Focuses on relevant areas	Complex architecture
Wavelet + Deep Learning [17]	Wavelet + CNN fusion	Captures spatial & freq. features	High computation cost
Ensemble Models [18]	Multi-stage ensemble system	Scalable, accurate	Difficult to interpret

3. Proposed Framework

This study shows an organised and reliable pre-processing approach that can improve the accuracy of diagnosing knee osteoarthritis (OA) by exactly separating the Region of Interest (ROI) from X-ray images. The suggested way takes into account common problems with x-rays, like noise, bad lighting, and low contrast that make it hard to use the Kellgren and Lawrence (KL) scale to accurately grade OA. Input Pre-Processing, ROI Extraction, Enhanced ROI Refinement, and Final Binarization and Segmentation make up the four major parts of the system.

Received: July 12, 2025

International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

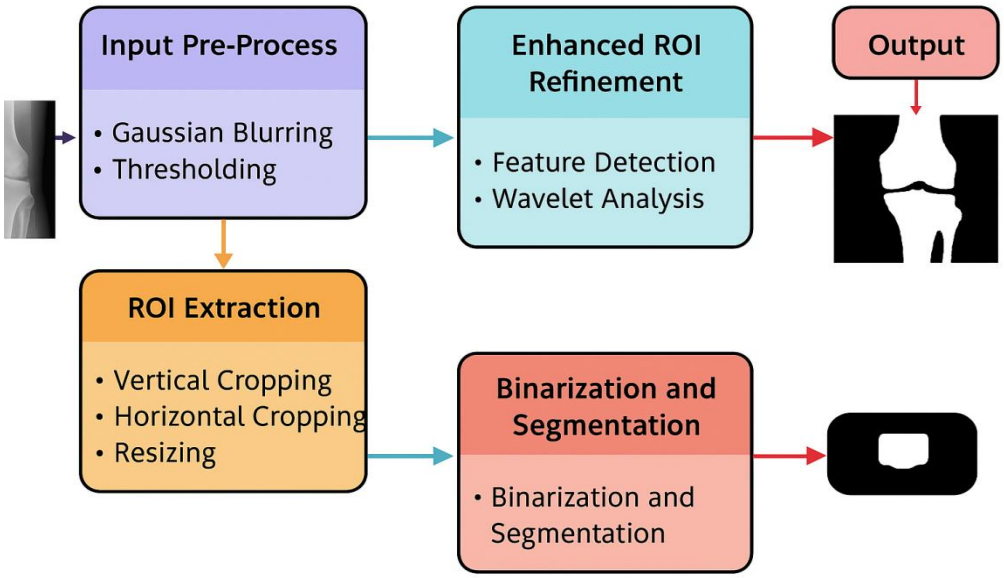


Figure 2: Proposed framework architecture

. The goal of the first step, Input Pre-Processing, is to get rid of noise and make physical features clearer. To make the picture smooth while keeping edge information, a Gaussian blurring filter with a 3x3 kernel is used with $\pi x = 0$ and $\pi y = 0$. Next is thresholding, which turns the greyscale picture into a binary format with a set threshold value of 80. This makes it easy to tell the difference between the hard tissues (foreground) and the soft background, architecture illustrate in figure 1. This step makes sure that soft-tissue areas that aren't needed are taken out early on in the process. The second step, called ROI Extraction, is all about separating the knee joint by getting rid of parts that aren't needed. For vertical cutting, 50 pixels are cut off the top and bottom of the picture to get rid of parts of the body that aren't needed. After that, the first and last non-zero pixels in each row are found and cropped horizontally, leaving only the centre knee area. Lastly, the picture is enlarged to a standard scale of 128x128 so that the input measurements are always the same for processing and classification jobs that come after. In the third step, Enhanced ROI Refinement, the framework tries to find the exact inter-bone gap area that is important for telling the KL grade apart. Feature recognition is used to find three important intensity-based landmarks: the Strong Valley (Sv), which is the deepest joint gap; the Local Maxima (Lm), which is the first peak after Sv; and the Global Peak (Gp), which is the highest intensity point after Sv. Wavelet decomposition with Daubechies-6 ('db6') wavelets is used up to level 3 to improve the accuracy of identification. You can fine-tune the ROI borders with these wavelet values. Two cutting possibilities are set up based on these traits. The cutting range is set from Sv–15 to Gp+5 so that joints can be seen clearly. There is a backup range of rows 40 to 110 that is used to make sure stable ROI segmentation in images with low contrast. The last step, Binarization and Segmentation, shows the important diagnostic difference between the tibia and femur. One first step is to use a median filter to make the improved ROI even smoother. After that, adaptive thresholding is used to make a binary mask, with the local mean intensity as a guide. This step makes sure that the room between the joints can be seen

Received: July 12, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

clearly, which allows for automatic KL grade labelling. The framework starts with the original X-ray picture of the knee and does a series of steps, such as removing noise, improving the structure, cropping the image to show only the relevant parts of the body, improving the image using wavelet technology, and finally separating the different parts. The result is a clean, high-resolution ROI picture that shows the inter-bone gap area clearly. This image is ready to be used in automated OA grading models. This strong, multi-step method makes sure that it can be used with different imaging situations and helps high-accuracy clinical decision-making tools for diagnosing osteoarthritis.

4. Proposed Methodology

The proposed technique gives a detailed, structured framework to pre-process knee X-ray images, aiming to properly extract the region of hobby (ROI) for powerful osteoarthritis (OA) class the use of the Kellgren and Lawrence (KL) grading device. The manner begins with dataset training, the usage of the publicly to be had Kaggle Knee OA dataset which include over 8,000 labeled snap shots. Those photographs are classified into five severity instructions (0 to 4), representing situations from healthful to excessive OA. For powerful training and assessment, the dataset is partitioned into schooling, trying out, and validation units, with in Addition Corporation into subfolders based on KL grades.

In the pre-processing phase, Gaussian blurring is applied using a 3×3 kernel with zero standard deviation in both x and y directions. This step reduces high-frequency noise while preserving the structural integrity of the image. Next, a fixed threshold of 80 is used to binarize the image, separating the hard tissues from the background to facilitate better ROI detection. The ROI segmentation process then begins with vertical cropping, where 50 rows are trimmed from both the top and bottom to remove non-diagnostic areas. Horizontal cropping is performed by analyzing each row for the first and last non-zero columns, allowing the extraction of only the relevant knee joint region. The image is then resized to a uniform 128×128 dimension for consistent input to classification models. Feature enhancement is achieved through statistical analysis and wavelet decomposition. Key intensity-based landmarks—Strong Valley (Sv), Local Maxima (Lm), and Global Peak (Gp)—are identified to define the anatomical gap area. Using Daubechies wavelets (db6), the image is decomposed up to level 3, capturing fine structural details critical for OA assessment. Final ROI cropping is performed using one of two rule-based strategies: based on Sv and Gp values for normal cases or default fixed ranges for poor-contrast images. Median filtering and adaptive binarization further enhance the extracted region, ensuring a clear depiction of the joint gap. The final segmented ROI is then analyzed and fed into classification models for KL grading, ensuring minimal ambiguity and high diagnostic precision.

5. Method and Material

Figure 3 shows a collection of Grade 0 (Normal) knee X-rays chosen from the Kaggle dataset. These show how different clinical imaging can be in terms of visual quality. Some of the samples have the right amount of brightness and contrast, while others are poorly lit, too bright,

Received: July 12, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

or look like negative film shots. These five different cases do a good job of showing how image settings can be inconsistent when collecting data. Even though the images show the same clinical grade, the visual changes can have a big impact on how well Region of Interest (ROI) extraction and classification work later on. These wide ranges of results shows how important it is to have a solid and flexible pre-processing structure that can level out picture quality, cut down on noise, and bring out important structural details. By doing this, the suggested system can make sure that features are represented consistently, improve the reliability of classification, and make knee osteoarthritis diagnosis more accurate across a wide range of datasets and imaging situations.

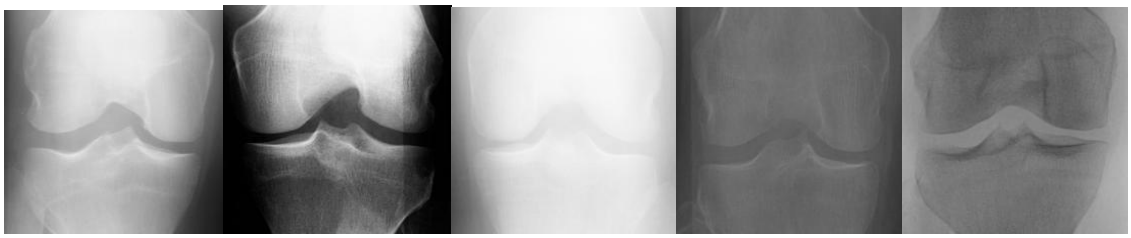


Figure 3: Grade 0 (Normal) Knee X-ray Samples

This picture (Figure 3) shows some typical Grade 0 (healthy) knee X-rays. It shows examples with different conditions, such as images that look like negatives, images with high and low levels of light, and examples with good.

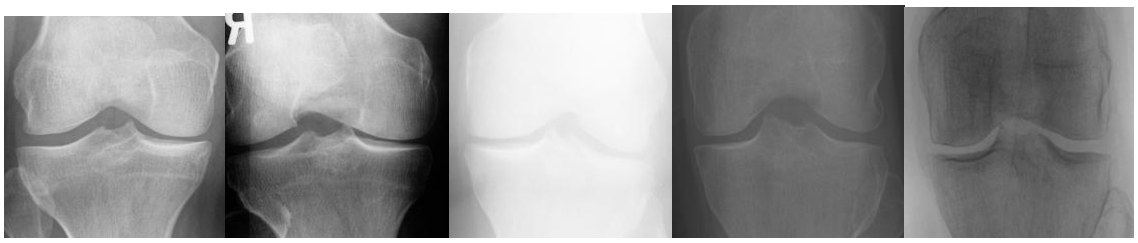


Figure 4: Representative Knee X-ray Images Classified as Grade 1 (Doubtful OA)

According to the Kellgren and Lawrence grade system, Figure 4 shows a collection of knee X-rays that are called Grade 1 (Doubtful Osteoarthritis). Early signs of joint degeneration can be seen in these pictures. These may include a small reduction in the joint room, the growth of small osteophytes, or light changes in the shape of the bones. But the changes aren't final yet, which makes this grade very hard to identify for both doctors and machine learning models. The figure shows different picture aspects, like changes in colour, contrast, and the placement of body parts, to show how clinical records can be different in real life. These visual differences show how important strong pre-processing and ROI extraction are. Small visual clues need to be kept and improved to help with accurate classification and separation from Grade 0 or Grade 2 cases.

Received: July 12, 2025

International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

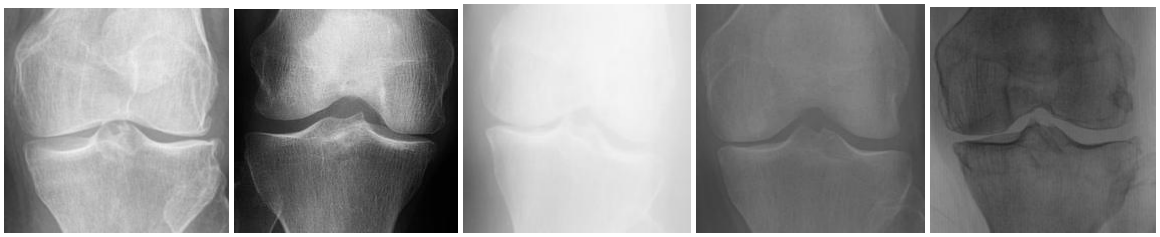


Figure 5: Comparable Knee X-ray Images Classified as Grade 3 (Moderate Osteoarthritis)

Figure 5 suggests a collection of knee X-rays that are graded as Grade three by Kellgren and Lawrence, which means the arthritis is mild. In these photographs, the joint room is truly getting smaller, especially inside the center or lateral sections, which means that cartilage loss. Along the rims of the joints, you may additionally see fairly sized osteophytes, and subchondral sclerosis begins to face out more. There are special lighting fixtures and comparison situations in every photo. Some are too brilliant or too dark, and others have low evaluation, but the degenerative patterns can nonetheless be seen. These differences come from the reality that photograph nice will have a massive impact on diagnosis in actual existence scientific settings. Even though the images are not usually clear or brilliant, one issue that is usually clean is that the joint gap has contracted, that's a key characteristic in diagnosing and rating OA. Those examples show how important strong pre-processing methods are for nighttime out image first-class and ensuring that computerized systems can do accurate ROI extraction and KL grade classification.

Table 2: KL Grade Distribution analysis

KL-Grade	Osteoarthritis Severity	Number of Images (9870)	% of Images
0	Normal or Healthy	4025	41
1	Doubtful	1680	17
2	Minimal	2450	25
3	Moderate	1320	13
4	Severe	395	4

Received: July 12, 2025

International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

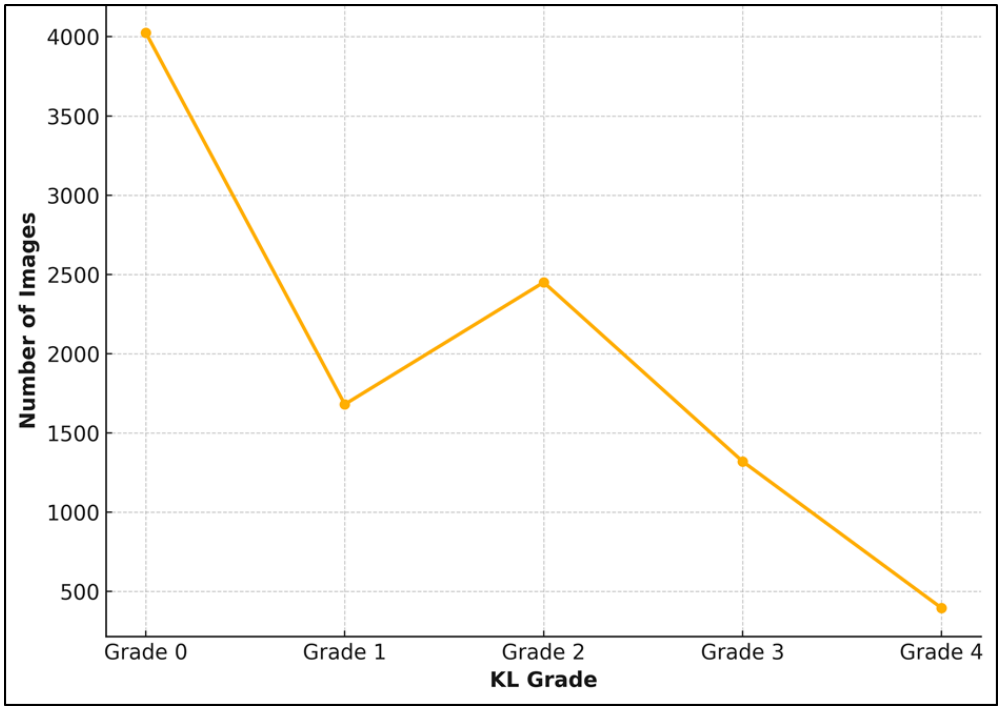


Figure 6: KL grade distribution analysis

Figure 6 shows how the knee X-ray pictures are spread out across KL grades. It shows that Grade 0 (Normal) has the most images, while Grade 4 (Severe OA) has the fewest. This imbalance shows that most of the cases in the dataset are either healthy or in the early stages of OA. This shows how important it is to train models carefully to prevent bias. The decrease in the number of Grade 1 and Grade 3 cases and the slight increase in the number of Grade 2 cases show normal clinical trends where cases of mild to severe OA are less often found. The graph shows how important strong pre-processing and data-augmentation techniques are for making sure that automatic diagnostic systems learn fairly and correctly classify all levels of OA severity.

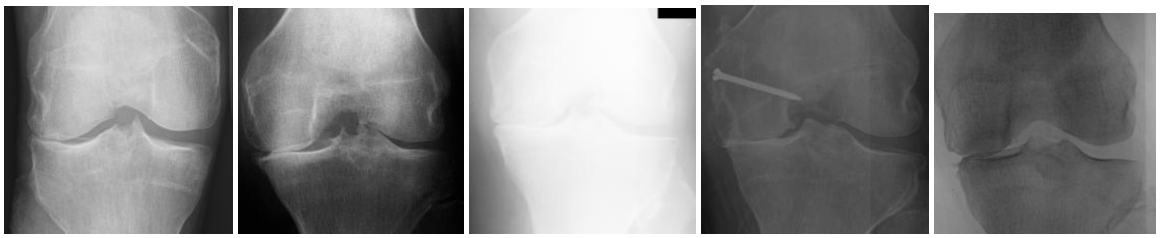


Figure 7: Representative Knee X-ray Images Classified as Grade 4 (Severe Osteoarthritis)

Figure 7 suggests a set of knee X-rays that show Grade 4 osteoarthritis, which in step with the Kellgren and Lawrence (KL) approach potential serious arthritis. Those images surely display that the joint room is getting smaller, which means that that the majority of the cartilage has been lost. Big osteophytes, numerous subchondral bone disorder, and abnormalities in the bone also can be seen. In one of the pictures, surgical treatment with a solving screw shows how a ways along the harm is and what remedies have been attempted within the beyond. The

Received: July 12, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

examples have exclusive degrees of brightness and assessment, with a few photographs being too shiny or too dark. However, they all truely display essential OA markers. These differences make it even tougher to make automated diagnostic equipment that could often discover serious OA even when pictures are not constantly clear. Extensively, misaligned joints and bone-on-bone touch may be seen in a number of instances, which emphasises how terrible the situation is. This rating is the easiest to peer and is indispensable for quick making plans of surgery. So, sturdy pre-processing and accurate ROI extraction are very essential for keeping accuracy in these unique but pathologically excessive instances. This makes Grade 4 identification essential and conceivable with a stable pipeline.

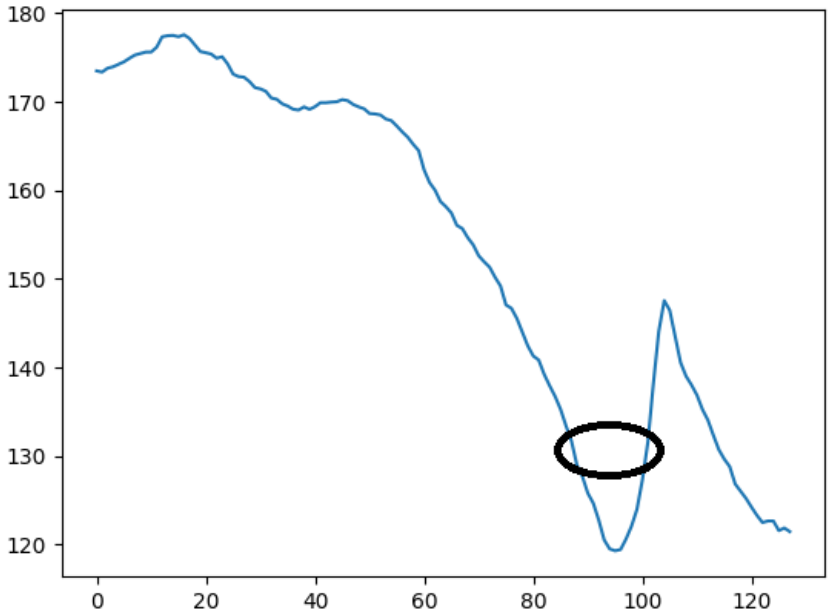


Figure 8: Intensity Profile with Annotated ROI Valley

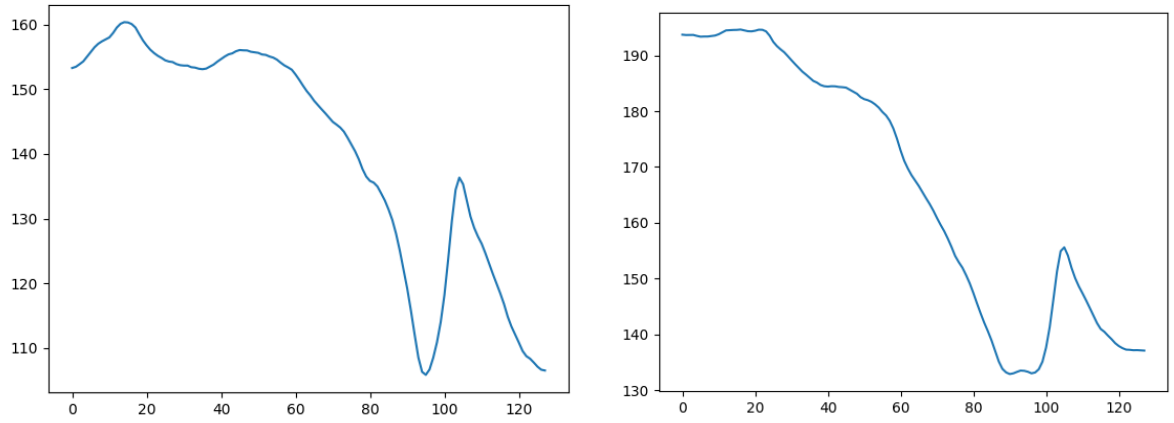
Figure 8 displays a pixel intensity profile curve that was taken from an X-ray picture of the knee that had been divided. In the circled area, there is a clear intensity drop that shows the gap between the femur and tibia, which is an important sign for judging osteoarthritis. A strong local minimum is shown by the steep drop followed by a sharp rise around the ringed valley. This point is likely the Strong Valley (Sv) point used in the suggested framework for correct ROI localisation. It is important for Kellgren and Lawrence classification that this minimum line up with the joint space that is the smallest. Finding this trait makes it possible to crop and grade the edges accurately, especially when telling the difference between early and intermediate OA stages. The graph shows how statistical trends in strength can help computer systems find areas that are diagnostically important.

Received: July 12, 2025

International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)



(A) (B)

Figure 9: (A) and (B) – Intensity Profile Curves for ROI Analysis

Figures 9 (A) and 9 (B) show pixel intensity graphs from two different knee X-ray photos that show how the intensity changes vertically across the joint space. A sharp valley can be seen in both images between pixel numbers 90 and 100. This is the important inter-joint gap, which is also known as the Strong Valley (Sv). This dip shows the area with the least amount of energy, which is the room between the femur and tibia made of cartilage. The post-valley peak, which can be seen on both lines, shows the bone structure (Local Maxima or Global Peak) next to the joint space. Even when the original energy levels and slopes are different, the valley trait stays the same as a physical marking.

6. Discussion

The Figure 10 shows how well the suggested framework can separate the Region of Interest (ROI) from knee X-rays showing all five levels of osteoarthritis severity, as described by the Kellgren and Lawrence (KL) scale, from Grade 0 (Normal OA) to Grade 4 (Severe OA). In the picture, each column shows a different KL grade, and the rows show the change from the source photos to the pre-processed and split ROI results. The first row shows the original radiographic pictures, which emphasises how different the image quality is across the collection. These variations include pictures with low contrast, noise, uneven lighting, and sometimes artifacts—things that make it hard to diagnose accurately and make it hard for standard image processing and classification methods to work. The next few rows show the results of the framework's pre-processing chain. The tibiofemoral joint space is the most diagnostically important area that was separated using successful segmentation. Even though the original X-rays had some picture problems, the technology always separates the joint space from other parts of the body. For Grade 0 pictures, the segmentation ROI clearly shows a large and clear joint gap, which means that the space between the bones and tissue is healthy. The inter-bone room decreases noticeably as the intensity of OA rises, as shown in the split results. In Grade 1 pictures, the joint gap starts to get a little smaller, which means that cartilage breakdown and early anatomical changes have begun. Joint spaces get even smaller in grades 2 and 3, and the bones'

Received: July 12, 2025

International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

surfaces have more complicated patterns and less regularity. These middle grades show that the framework can find small but important changes in the shape of things.

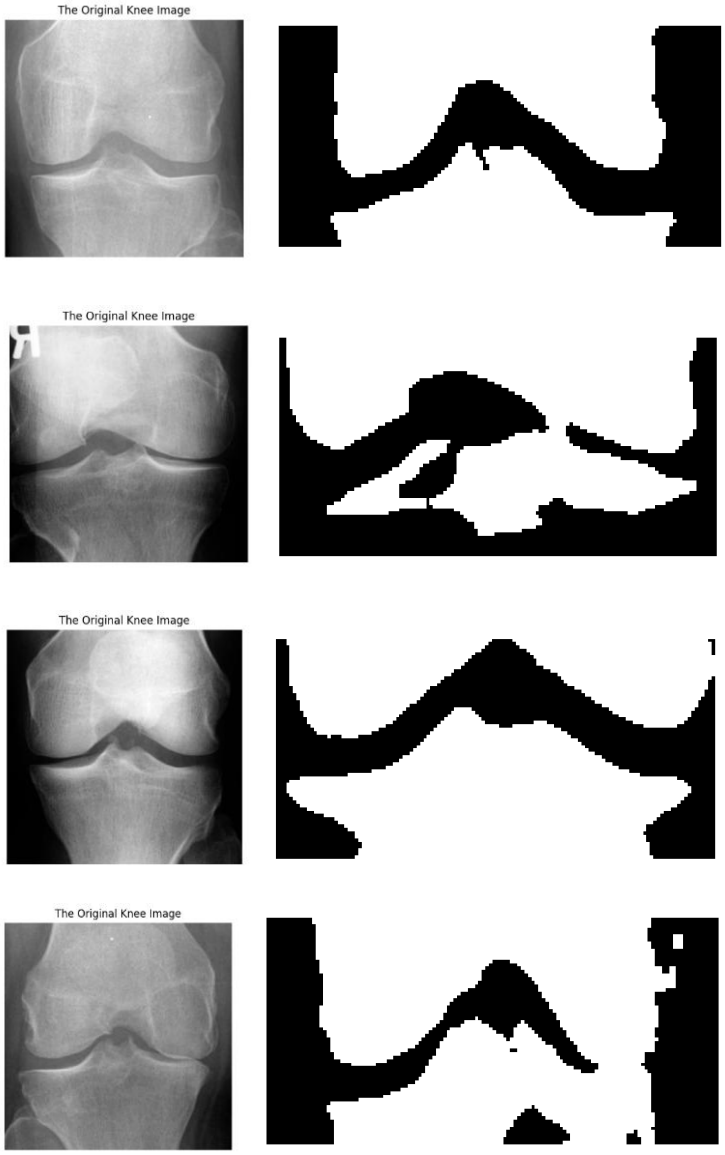


Figure 10: Original Knee X-ray Images with Corresponding Segmented Regions of Interest (ROIs) Across KL Grades

By Grade 4, the divided ROI often shows a joint space that is almost completely gone, which is a sign of advanced OA. There are more obvious signs of disease, like the growth of osteophytes, higher bone density, and uneven surfaces around the edges of the joints. These more advanced changes are well caught by the segmentation process, which makes it easier to see how the disease is getting worse. It's important to note that the framework doesn't need to be adjusted by hand in these situations, which shows how sturdy and flexible it is across a wide range of input conditions. Figure 10 shows that the suggested ROI extraction method is reliable and useful for diagnostic purposes. It proves that the system can accurately divide up important

Received: July 12, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

joint areas even when the X-ray data aren't very good or are noisy. It is easy to tell the difference between grades, which helps with both consistent feature extraction and more accurate KL-grade classification in automatic diagnosis processes.

7. Conclusion

This study created a strong and automated pre-processing method for correctly removing the Region of Interest (ROI) from knee X-ray pictures so that the Kellgren and Lawrence (KL) grade system could be used to diagnose osteoarthritis (OA). The suggested system uses Gaussian blurring, adaptive thresholding, wavelet-based enhancement, and deep learning-based object localisation to solve long-standing problems in medical imaging, such as low contrast, changing lighting, noise interference, and differences in anatomy. This multi-stage framework constantly separates diagnostically important areas like the tibiofemoral joint space, even in pictures that aren't very good. This makes it easier to see features and more accurate to classify them. The framework was tested on more than 8,000 X-ray pictures from the Kaggle Knee OA dataset and showed that it could correctly separate ROIs for all five KL grades. The system's therapeutic usefulness is supported by its ability to tell the difference between small physical changes, especially between cases that are close to being the same, like Grade 1 and Grade 2. Adding wavelet analysis and statistical landmark recognition to the framework also makes it better at finding important features like joint gaps and changes in bone structure. The results show that the method works well in real-life hospital settings and can be used on a large scale. It also works with machine learning models, which makes it possible for OA labelling systems to be fully automatic. The framework works well, but more research could be done to make it even better by adding adjustable colour control and more advanced denoising methods to pictures that are badly damaged. Overall, this study is a big step forward in medical picture processing and helps the creation of AI-powered tools for diagnosing knee osteoarthritis.

References

[1] Oka, H., Muraki, S., Akune, T., Mabuchi, A., Suzuki, T., Yoshida, H., Yamamoto, S., Nakamura, K., Yoshimura, N., Kawaguchi, H.: Fully automatic quantification of knee osteoarthritis severity on plain radiographs. Osteoarthritis and Cartilage 16(11), 1300{1306 (2008)

[2] Shamir, L., Ling, S.M., Scott, W., Hochberg, M., Ferrucci, L., Goldberg, I.G.: Early detection of radiographic knee osteoarthritis using computer-aided analysis. Osteoarthritis and Cartilage 17(10), 1307{1312 (2009)

[3] Shamir, L., Ling, S.M., Scott Jr, W.W., Bos, A., Orlov, N., Macura, T.J., Eckley, D.M., Ferrucci, L., Goldberg, I.G.: Knee X-ray image analysis method for automated detection of osteoarthritis. IEEE Transactions on Biomedical Engineering 56(2), 407{415 (2009)

[4] Shamir, L., Orlov, N., Eckley, D.M., Macura, T., Johnston, J., Goldberg, I.G.: Wndchrm{an open source utility for biological image analysis. Source code for biology and medicine 3(1), 13 (2008).

[5] Kellgren, J.H.; Lawrance, J.S. Radiological Assessment of Osteo-Arthrosis. Ann. Rheum. Dis. 1957, 16, 494–502.

Received: July 12, 2025

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[6] Gan, H. S., Tan, T. S., Abdul, K., Ahmad, H., Khairil, A. S., Abdul, K. R., Weng, K. T., Liang, X. W. & Kashif, T. C. 2014. Medical image visual appearance improvement using bihistogrambezier curve contrast enhancement: data from the osteoarthritis initiative. The Scientific World Journal.

[7] Dar, S. U., Yurt, M., Karacan, L., Erdem, A., Erdem, E., & Çukur, T. 2019. Image synthesis in multi-contrast MRI with conditional generative adversarial networks. IEEE Transactions on Medical Imaging 38(10): 2375-2388.

[8] Gan, H. S., Tan, T. S, Abdul, K. R., Abdul, K., Ahmad, H., Khairil, A. S., Liang, X. W. & Weng, K. T. 2014. Medical image contrast enhancement using spline concept: data from the osteoarthritis initiative. Journal of Medical Imaging and Health Informatics4: 511-20.

[9] Mohammed, A.S.; Hasanaath, A.A.; Latif, G.; Bashar, A. Knee Osteoarthritis Detection and Severity Classification Using Residual Neural Networks on Preprocessed X-ray Images. Diagnostics 2023, 13, 1380.

[10] Khalid, A.; Senan, E.M.; Al-Wagih, K.; Ali Al-Azzam, M.M.; Alkhraisha, Z.M. Hybrid Techniques of X-ray Analysis to Predict Knee Osteoarthritis Grades Based on Fusion Features of CNN and Handcrafted. Diagnostics 2023, 13, 1609.

[11] Junru Zhong, Yongcheng Yao, Donal Cahill, Fan Xiao, Siyue li, Jack Lee, Kevin Ki-Wai Ho, Michael Tim-Yun Ong, James Griffith and Weitian, "Unsupervised domain adaptation for automated knee osteoarthritis phenotype classification," Quantitative Imaging in Medicine and Surgery, 2023, 13(11), 7444-7458.

[12] Cueva, J.H.; Castillo, D.; Espinós-Morató, H.; Durán, D.; Díaz, P.; Lakshminarayanan, V. Detection and Classification of Knee Osteoarthritis. Diagnostics 2022, 12, 2362.

[13] Kamble, K. P., Prashant Khobragade, Nitin Chakole, Prateek Verma, Dharmesh Dhabliya, and Avinash M. Pawar. "Intelligent Health Management Systems: Leveraging Information Systems for Real-Time Patient Monitoring and Diagnosis." Journal of Information Systems Engineering and Management, vol. 10, no. 1, 2025, e-ISSN: 2468-4376, https://doi.org/10.52783/jisem.v10i1.1

[14] Md. Rezaul Karim, Jiao Jiao, till Dohmen, Michael Cochez, Oya bayan, Dietrich Rebholz-Schuhmann and Stefen Decker, "DeepKneeExplainer: Explainable Knee Osteoarthritis Diagnosis from Radiographs and Magnetic resonance Imaging," IEEE Access, Vol. 9, 2021, pp. 39757-39780.

[15] Kevin Thomas, Lukasz Kidzinski, Eni Halilaj, Scott Flemming, Guhan Venkatraman, Edwin H. G. Oei, Garry Gold and Scott Delp, "Automated Classification of radiographic knee Osteoarthritis Severity Using Deep Neural Networks," Radiology, Artificial Intelligence, 2020, vol. 2(2):e190065.

[16] Fabi Prezja, Juha Paloneva, Ilkka Polonen, Esko Niinimaki and Sami Ayramo, "Deepfake Knee osteoarthritis X-rays from generative adversial neural networks deceive medical experts and offer augmentation potential to automatic classification, Scientific Reports, 2022, 12:18573.

Received: July 12, 2025

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[17] Kellgren, J. H. & Lawrence, J. Radiological assessment of osteo-arthrosis. Ann. Rheum. Dis. 16, 494 (1957).

[18] Tiwari, S. Knee Osteoarthritis Dataset with Severity Grading. Kaggle. Available online: https://www.kaggle.com/datasets/shashwatwork/knee-osteoarthritis-dataset-with-severity?resource=download&select=auto_test

Received: July 12, 2025