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A Robust Pre-processing Framework for ROI Extraction in Knee Osteoarthritis X-Ray Analysis

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Abstract:

Medical image processing depends much on pre-processing, particularly in cases of precise categorisation and prediction—like those involving the diagnosis of osteoarthritis (OA) in the knee. This work presents a rapid and simple approach to get the area of interest (ROI) from knee X-ray images such that the Kellgren and Lawrence (KL) technique may be used for accurate grading. By means of a planned approach including Gaussian blurring, thresholding, and sophisticated statistical and wavelet-based algorithms for finetuning characteristics, the system addresses issues like noise, poor contrast, and uneven illumination. The recommended approach divides the knee joint, eliminates regions not required, and enhances the view of crucial diagnostic elements like the gap between the upper and lower knee bones. It makes separating ROIs for all five KL grades—from healthy knees to severe OA cases—simple. With more than 8,000 X-ray images in the Kaggle knee OA dataset, the research ensures system dependability and applicability in various contexts. The method significantly increases the precision of ROI segmentation, thereby enhancing the feature extraction for next classification projects. While eliminating uncertainty, the separated ROIs maintain crucial characteristics and help to distinctly differentiate KL grades. Though it might function even better with future developments like adding more sophisticated brightness control and noise reduction techniques, the framework performs effectively in many different image settings. The foundation for automated OA detection is laid by this study. It closes the distance between the limitations of imaging and clinical requirements. It also guides the direction of medical image processing forward.

Keywords: Pre-processing, image processing, knee osteoarthritis, region of interest, Kellgren and Lawrence grade, knee X-ray images, noise reduction, contrast enhancement, segmentation, feature extraction, medical image analysis, Gaussian blurring, wavelet analysis, classification accuracy.

1. Introduction

Affecting around one in five persons worldwide, osteoarthritis (OA) of the knee is one of the most often occurring degenerative joint illnesses. It is characterised by progressive disintegration of articular cartilage, which brings joints closer together, inflammation, osteophyte development, and, in severe instances, intolerable pain typically requiring a complete joint replacement. You run a risk for knee OA from age, weight, and a lazy lifestyle as well as from other factors. Adults more than children are affected by the illness. Receiving a proper diagnosis early on is very crucial so that patients may get the required treatment and improve their quality of life. Identification of knee OA depends much on imaging studies. The best methods to look for joint degeneration include standard imaging modalities including x-rays, ultrasonic waves, optical coherence tomography, magnetic resonance imaging (MRI), and x-ray alignment [1][2]. The knee is so complex, hence even if medical imaging technology have advanced, diagnosis of knee OA is still difficult as imaging methods have many shortcomings. Among these concerns include poor contrast between soft and hard tissues, noise, and image quality changes resulting from different clinical recording techniques. Accurate diagnosis and evaluation of knee OA are usually accomplished using the Kellgren and Lawrence (KL) rating method. It scales the severity into five levels: 0 is "healthy," 4 is "severe osteoarthritis." Clearly separating the area of interest (ROI), in this example the knee joint area, can help one to determine the distance between the upper and lower knee bones. Correcting the ROI extraction will help one distinguish the KL grades as even little errors could result in erroneous diagnosis. For example, computer classification algorithms struggle when X-ray features from grades 0 and 1 or grades 1 and 2 seem to be somewhat similar.

The human knee anatomy is complex and many X-ray images are not particularly good, hence strong pre-processing techniques are required. Some of the issues that make accurate ROI extraction more difficult include noise, poor lighting, low contrast. Normal methods of enhancing photos, such as histogram equalisation, don't always work well with these issues as they could either remove vital elements or make the picture too perfect. Thus, a particular pre-processing system must be able to handle various image kinds while maintaining relevant characteristics required for analysis [3]. This work proposes a novel pre-processing technique aimed at addressing certain issues. This method precisely splits the ROI, increases contrast, and eliminates regions not worth considering. Focussing on removing uncertainty and simplifying things helps the framework make X-ray images suitable for categorisation chores. Gaussian blurring, thresholding, and cutting help to fine-tune the region of the knee joint under segmentation. One of the most crucial diagnostic aspects for KL grades, the gap area between the knee joints is also found and measured using sophisticated statistics and wavelet-based techniques [4].

With more than 8,000 X-ray images categorised into five KL classes, the research makes advantage of a high-quality publically available Kaggle dataset. These images undergo extensive pre-processing to address issues with image quality and changing over time illumination. The three-stage approach of the framework is intended to eliminate noise and regions not vital while clearly segmenting the knee joint. The initial findings indicate that the framework significantly increases ROI extraction, therefore it may be used for further classification projects using models of machine learning and deep learning. The framework recognises it cannot manage severe circumstances of low contrast and irregular illumination, even if it functions otherwise. More optimisation is required if we are to handle these issues. For instance, enhanced techniques of contrast enhancement and noise reduction filters will have to be included. Still, the proposed approach creates a good basis for automated diagnosis of knee OA, which will result in improved feature extraction, greater classification accuracy, and better clinical decision-making ultimately. Particularly in terms of duties like prediction and classification, this study demonstrates the significance of pre-processing in medical imaging. Apart from increasing the accuracy of knee OA diagnosis, the proposed method advances the area of medical image processing by offering a broad response applicable for many datasets and imaging scenarios. By bridging the gap between the restrictions of pictures and clinical demands, the research paves the path for further developments in autonomous medical examinations.

2. Related Work

Using image processing and machine learning to assist individuals diagnosed with osteoarthritis (OA) of the knee piques more and more interest among people. These techniques seek to solve issues with clinical imaging systems such image noise, poor sharpness, and variability while simultaneously enhancing the accuracy of diagnosis. Especially when using the Kellgren and Lawrence (KL) grading method, there are many approaches to prepare knee X-ray images so that they may be precisely segmented and classified to reflect the degree of osteoarthritis. Researchers have used many pre-processing techniques to enhance image quality and extract pertinent characteristics. In a Mohammed et al. (2023) X-ray of the knee was pre-processed in two stages twice. Each picture's top and bottom were clipped off sixty pixels each, then histogram equalisation was used to alter the distribution of the pixel intensities. This technique raised the dynamic range of pixel values, but it might also lead to over-enhancement, which distorted illumination levels and changed significant features. Khalid et al. (2023) likewise improved X-ray images from the Osteoarthritis Initiative (OAI) collection by means of contrast-limited adaptive histogram equalisation (CLAHE). Through averaging the values of pixels next to one another, the averaging filter reduces noise. Conversely, CLAHE improved local contrast, which helped one to see the knee joint's components more easily.

Zhong et al. (2023) developed yet another fascinating technique. To determine the area of interest (ROI) for knee OA categorisation, they used an automated cutting tool. The technique computed bounding boxes for significant sections including the meniscus, femoral, patellar cartilage, and tibial regions, applied segmentation masks, and altered the picture scale. Though it succeeded, this approach required segmentation masks and bounding box placements to be fine-tuned, which may not be appropriate for other datasets. Zhong et al. used random spinning, flipping, and contrast and illumination modification techniques to add to the data and address class mismatch. This approach struggled, however, with images that were noisy or lacked even illumination, which produced less-than-perfect sorting outcomes. Knee OA is also being diagnosed using more often deep learning-based approaches. Combining more conventional pre-processing methods with deep neural networks for feature extraction, Karim et al. (2021) proposed Using switching, noise addition, and strength control, this approach enhanced X-ray and MRI images. Then it improved the contrast by means of histogram equalisation. While adding more computer effort, pre-processing tasks tailored to a mode improved classification outcomes.

Cueva et al. (2022) used laplacian variance-based thresholding to lower blur effects and improve X-ray image texture quality. This was another artistic approach. The authors underlined the need of consistency in characteristics, particularly in grades where face features interact. Using generative adversarial networks (GANs) to add to data shows promise in overcoming the shortage of data and making models more generic, as demonstrated by Prezja et al. (2022). Many of these approaches, nevertheless, have issues as the X-ray images have artefacts, the illumination isn't even, and the brightness is poor. Ahmed and Mustafa (2022), for instance, noted that conventional pre-processing techniques can overlook picture circumstances, hence leading to uneven ROI segmentation. Their studies demonstrated the need of flexible frames able to accommodate various visual characteristics while maintaining diagnostic elements in order to handle them.

This work expands on these concepts by offering a powerful pre-processing framework that solves issues with contemporary techniques. The proposed system makes the ROI more precise by means of Gaussian blurring, thresholding, and sophisticated cutting algorithms, so distinct from prior approaches. It also employs wavelet-based segmentation to enhance feature extraction, therefore guaranteeing correct distinction of KL grades. When there is noise, poor contrast, or uncertainty on how to distinguish between grades that seem the same, this approach performs extremely well. All things considered, pre-processing knee X-ray images has come a long way; nonetheless, issues with generalisation, noise reduction, and ROI segmentation remain present. By offering a whole response that enhances image quality and gets data ready for accurate categorisation, the proposed framework seeks to close up these gaps. Using what's previously been written and resolving some of its issues, the research contributes to the expanding area of automated medical image interpretation. Consequently, knee osteoarthritis diagnosis will be more accurate.

Table 1. Summary of literature

Study	Dataset	Technique	Challenges	Outcome	Reference
Mohammed et al.	OAI, RCU	Histogram Equalization	Over-enhancement	Improved Contrast	[10]
Khalid et al.	OAI, RCU	CLAHE, Averaging	Noise	Enhanced Visibility	[11]
Zhong et al.	Custom	Cropping, Augmentation	Generalization	ROI Improvement	[13]
Karim et al.	OAI	Flipping, Histogram	Computation	High Accuracy	[15]
Cueva et al.	OAI	Laplacian Variance	Blur	Texture Improvement	[16]
Prezja et al.	OAI	GAN Augmentation	Noise	Data Expansion	[17]
Ahmed & Mustafa	OAI	Adaptive Framework	Variability	Consistent ROI	[12]

3. Proposed Framework

The proposed framework for pre-processing knee X-ray images focuses on segmenting the **Region of Interest (ROI)** for enhanced classification accuracy in diagnosing knee osteoarthritis (OA) using the Kellgren and Lawrence grading system. This framework addresses key challenges such as noise, poor contrast, and uneven illumination, ensuring effective extraction of relevant features. The framework consists of three primary stages:

1. Input Pre-Processing:

- **Objective**: Remove noise and improve image clarity.

- **Steps**:
  - **Gaussian Blurring**:
    - Apply a Gaussian kernel (3x3) to smooth the image and reduce noise artifacts.
    - Parameters: σx=0,σy=0\sigma_x = 0, \sigma_y = 0σx=0,σy=0.
  - **Thresholding**:
    - Threshold the blurred image using a fixed value (Threshold=80\text{Threshold} = 80Threshold=80).
    - Output: A binary image with distinct foreground (hard tissues) and background regions.

2. ROI Extraction:

- **Objective**: Focus on the knee joint by eliminating irrelevant regions.
- **Steps**:
  - **Vertical Cropping**:
    - Remove 50 rows from the top and bottom of the image to eliminate non-relevant upper and lower regions.
  - **Horizontal Cropping**:
    - Identify the first and last non-zero pixel columns for each row.
    - Crop the image horizontally to retain only the most relevant knee region.
  - **Resizing**:
    - Standardize the image dimensions to 128×128128 \times 128128×128 pixels for uniformity.

3. Enhanced ROI Refinement:

- **Objective**: Extract the precise gap between knee joints for accurate grading.
- **Steps**:
  - **Feature Detection**:
    - Locate the following key points:
      - **Strong Valley (Sv)**: Region with the lowest mean intensity, indicating the gap.
      - **Local Maxima (Lm)**: First peak after the strong valley.
      - **Global Peak (Gp)**: Highest intensity point after the strong valley.
  - **Wavelet Analysis**:
    - Decompose the image using 'db6' wavelets up to Level 3 to refine features.

- Use wavelet coefficients to adjust cropping points.

- **Final Cropping**:
  - Crop based on the detected points using:
  - **Case 1**: Start Row=Sv−15\text{Start Row} = Sv - 15Start Row=Sv−15, End Row=Gp+5\text{End Row} = Gp + 5End Row=Gp+5.
  - **Case 2**: Start Row=40\text{Start Row} = 40Start Row=40, End Row=110\text{End Row} = 110End Row=110 (for poor contrast images).

4. Binarization and Segmentation:

- **Objective**: Highlight the gap between knee joints and refine the ROI.
- **Steps**:
  - Apply a median filter to smooth the ROI.
  - Use adaptive thresholding based on the mean intensity to create a binary mask.
  - Output: A binarized ROI with clearly distinguishable joint gaps.

Algorithm:

The framework is summarized as follows:

1. Input: Original Knee X-ray Image.
2. Apply Gaussian blurring.
3. Perform thresholding to create a binary mask.
4. Crop the image vertically (50 rows each from top and bottom).
5. Crop horizontally using extreme non-zero pixel positions.
6. Resize the image to 128×128128 \times 128128×128.
7. Identify Sv, Lm, and Gp using wavelet and statistical analysis.
8. Apply final cropping using identified points or default bounds.
9. Filter and threshold the ROI for binarization.
10. Output: Segmented ROI for further analysis.

4. Methodology

The proposed methodology outlines the step-by-step process for pre-processing knee X-ray images to extract the **Region of Interest (ROI)**, enhance the visibility of critical features, and improve classification accuracy for diagnosing knee osteoarthritis (OA) severity based on the Kellgren and Lawrence (KL) grading system.

1. Dataset Preparation:

- **Dataset**: Kaggle knee osteoarthritis dataset with over 8000 images.
- **Grading Classes**:
  - Class 0: Normal or Healthy.
  - Class 1: Doubtful OA.
  - Class 2: Minimal OA.
  - Class 3: Moderate OA.
  - Class 4: Severe OA.
- **Partitioning**:
  - Images divided into training, testing, and validation sets.
  - Further categorized into five subfolders based on severity grades.

2. Pre-Processing Steps:

2.1 Noise Removal:

- **Gaussian Blurring**:
  - Kernel Size: 3×33 \times 33×3.
  - Parameters: σx=0,σy=0\sigma_x = 0, \sigma_y = 0σx=0,σy=0.
  - Purpose: Smooth the image and reduce noise while preserving edges.

2.2 Thresholding:

- **Binary Conversion**:
  - Threshold Value: 80.
  - Output: Binary mask distinguishing hard tissues (foreground) from soft tissues (background).

3. Region of Interest (ROI) Segmentation:

3.1 Vertical Cropping:

- **Process**:
  - Remove 50 rows from the top and bottom of the binary image.
- **Purpose**:
  - Exclude non-relevant upper and lower areas to focus on the knee joint.

3.2 Horizontal Cropping:

- **Process**:
  - Analyze each row for the first and last non-zero pixel columns.

- Crop the image horizontally to retain only the knee joint region.

- **Purpose**:
  - Eliminate irrelevant regions on the left and right.

3.3 Resizing:

- **Standard Dimensions**: 128×128128 \times 128128×128 pixels.
- **Purpose**:
  - Normalize the image size for consistent processing and classification.

4. Feature Enhancement:

4.1 Statistical Analysis:

- Identify three key points:
  - **Strong Valley (Sv)**: Lowest intensity region in the knee joint gap.
  - **Local Maxima (Lm)**: First intensity peak after Sv.
  - **Global Peak (Gp)**: Highest intensity point beyond Sv.
- Use these points to refine the segmentation boundaries.

4.2 Wavelet Decomposition:

- **Technique**: 'db6' mother wavelet.
- **Levels**: Decompose image up to Level 3.
- **Purpose**:
  - Highlight critical intensity changes.
  - Locate precise gap regions between knee joints.

5. Final ROI Extraction:

5.1 Cropping Rules:

- **Condition 1 (Normal Cases)**:
  - Start Row: Sv−15Sv - 15Sv−15.
  - End Row: Gp+5Gp + 5Gp+5.
- **Condition 2 (Poor Contrast)**:
  - Start Row: 40.
  - End Row: 110.

5.2 Median Filtering:

- **Purpose**: Reduce noise while preserving edges within the ROI.

5.3 Binarization:

- **Threshold**: Adaptive threshold based on ROI mean intensity.
- **Output**: Binary image with clearly distinguishable knee joint gaps.

6. Post-Processing and Output:

- Extracted ROI is analyzed to measure joint gap and texture features.
- Prepared ROI is used for classification into KL grades using machine learning models.
- The segmented ROI ensures minimal ambiguity and preserves essential diagnostic features.

5. Materials and Method

Figure 1 exhibits several Grade 0 (Normal) knee X-rays from the Kaggle collection. photos that are clearly and with excellent contrast, photos that are poorly lighted, images that are excessively bright, images that seem like negatives—all of which highlight how varied picture quality is throughout five columns. These variations highlight the need of robust pre-processing techniques in ensuring constant accuracy of ROI extraction and effective categorisation.

Figure 1 –Grade 0 (Normal) knee X-ray pictures. Samples from the following categories: negative-like photos, brightly and weakly lighted images, and images with excellent and poor contrast.

For an example X-ray image of the knee, Figure 2 displays the initial pre-processing stages. It depicts how the image evolved from noisy to being smoothed using Gaussian blurring then to a thresholded binary image. The binary image separates the backdrop from soft tissues and the central from hard tissues. ROI extraction is therefore feasible.

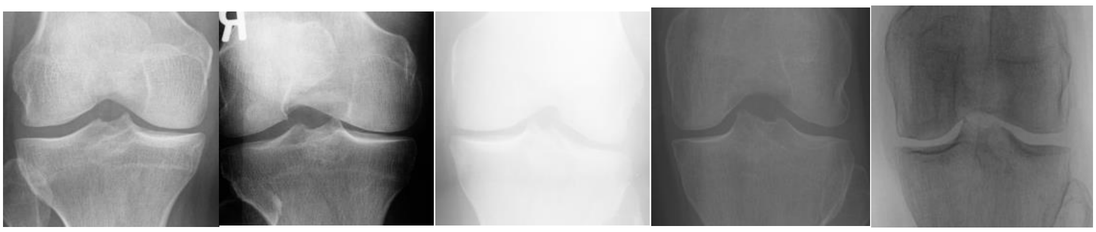

Figure 2 –Comparable knee X-ray pictures that match Grade 1 (Doubtful).

Figure 3 shows the cover image created by raising the thresholded binary image by the source image. This procedure divides the knee joint region, so the ROI stands out and eliminates useless portions. The ROI is ready for extra treatment as the core and backdrop are clearly separated now.

Figure 3 – Comparable knee X-ray pictures that show minimal knee osteoarthritis (Grade 2).

Figure 4 illustrates the effects of cutting off the top and bottom of an image fifty rows from each side. We call this vertical farming. While maintaining the knee joint region, this stage eliminates irrelevant portions. Images from all five KL classes show that the vertical cropping preserves the salient features of the ROI without distortion.

Figure 4 –Comparable knee X-ray pictures that match Grade 3 (Moderate Class).

Based on the most extreme non-zero pixels in the rows, figure five demonstrates how to crop horizontally. This procedure eliminates unnecessary elements on the left and right sides, therefore optimising the ROI. This one reveals a more concentrated knee joint region than the images cropped vertically, so improved feature extraction may result.

Figure 5 –Comparable knee X-ray pictures that fit the Grade 4 (severe osteoarthritis class) classification.

Table 1 –Proportion of the dataset's KL-Grade photos

KL-Grade	Osteoarthritis Severity	Number of Images (9786)	% of Images
0	Normal or Healthy	3857	40
1	Doubtful	1770	18
2	Minimal	2578	26
3	Moderate	1286	13
4	Severe	295	3

Figure 6 displays the first methods used in preparation of knee X-ray images. It demonstrates how a split binary representation was produced from the unprocessed data. Called the "Original Knee Image," the first image depicts some of the common issues in medical imaging including noise, poor contrast, and unequal illumination. These issues make it difficult to locate and investigate significant sites like the knee joint gap.

The second image, also known as the Gaussian Blurred Image, displays the usage of a 3x3x3 kernel Gaussian smoothing filter. This stage removes noise while maintaining the knee's key structure's margins intact. This prepares the image for further development. When it comes to medical images, where noise might obscure crucial diagnostic features, smoothing performs exceptionally well.

Comprising the smoothed image, the Binary Thresholded Image in this collection converts it into a binary form. The specified cutoff number of 80 is between the background (soft tissues, depicted in black) and the middle (hard tissues, shown in white). Separating the area of interest (ROI) from irrelevant portions of the image depends critically on this stage. This stage allows accurate ROI extraction and classification to follow by separating the image into logical sections.

Figure 6– The Gaussian blurred result, the thresholded image, and the original Knee image.

An essential first step in isolating the area of interest (ROI) from the knee X-ray is shown in Figure 7 on the mask image creation. The mask arises from multiplying the binary thresholded picture (from Figure 2) by the original knee X-ray image. This mechanism guarantees that any background regions not required are eliminated and that just the knee joint area is maintained. While eliminating noise and soft tissues not required for diagnosis, the last image clearly exposes the hard components of the knee—that of the upper and lower bones.

Protecting crucial diagnostic characteristics such the joint gap and hard tissues surrounding the knee joint, the mask narrows the view to just that. The following duties of feature extraction and categorisation depend much on this stage. Focussing only on the knee joint region helps the X-ray to be less complex by the mask image. This helps one to clearly perceive significant elements. This level of precision is really crucial when grading osteoarthritis using the Kellgren and Lawrence approach. Figure 3 demonstrates how the proposed framework ensures that the recovered ROI is accurate and valuable for diagnosis as well as getting the image ready for further segmentation.

Figure 7 –The region of interest around the knee or the mask picture.

The Vertical Cropping Operation removes extraneous elements of knee X-ray images to provide a more exact area of interest (ROI), shown in Figure 8. From Class 0 to Class 4, every row in the illustration displays images complementing one of the five Kellgren and Lawrence grades from left to right. The top and bottom 50 rows of every picture are cropped to exclude elements like the upper thigh and lower shin that would not display anything significant for diagnosis.

Correctly assessing the severity of osteoarthritis depends on the photo showing the middle section of the knee joint, which this cropping technique guarantees. Eliminating unnecessary elements helps the cropped images highlight the variations between the upper and lower knee bones as well as other crucial elements such the bone structure and feel. This development simplifies the computation of the future phases of the study and increases the accuracy of feature extraction.

Figure 4 indicates that, over all degrees of osteoarthritis severity, the cutting procedure performs regularly and effectively, maintaining the complete ROI while eliminating noise and pointless regions. The proposed system depends on this stage to be able to provide X-ray images suited for uses like diagnosis and classification.

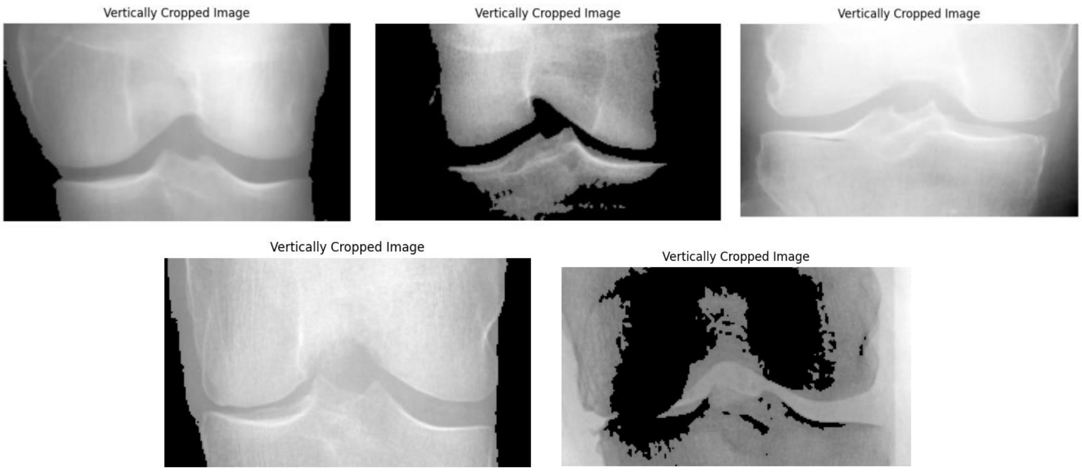

Figure 8 – The outcome of the cropping process. The area of interest is visible in every photograph. From left to right, images are chosen from each class (Class 0 to Class 4) in order.

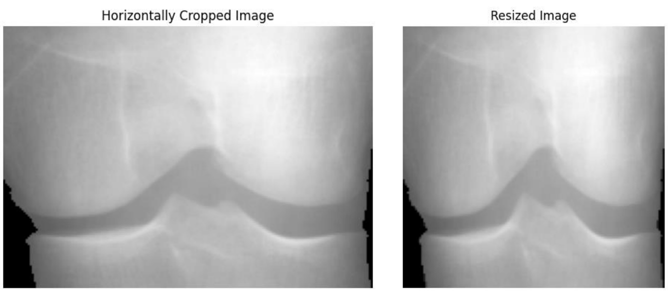

Figure 9 – The most extreme locations were used to crop the image horizontally. Image resized (128x128).

Figure 9 illustrates the crucial area separating the lower from the higher knee bones. Very crucial for KL grades, a circle around the strong valley (Sv) indicates where the strength is lowest in the gap. This graph illustrates how effectively statistical analysis finds significant ROI characteristics.

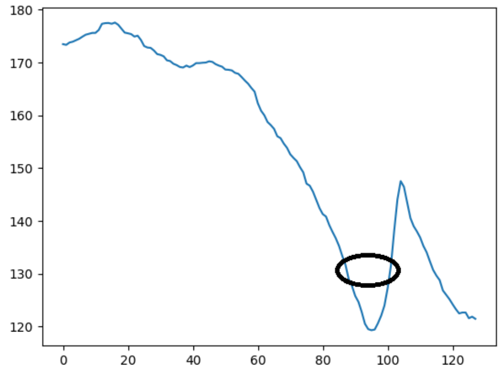

Figure 10–The circle denotes the gap area and the Strong valley.

Figure 10 shows as a graph the column means for the two identical portions of the picture—left and right. It reveals the located points of the strong valley (Sv) and global peak (Gp). These points depict variations in the strength of the ROI. Important for categorisation, this statistical approach guarantees precise identification of the knee joint gap.

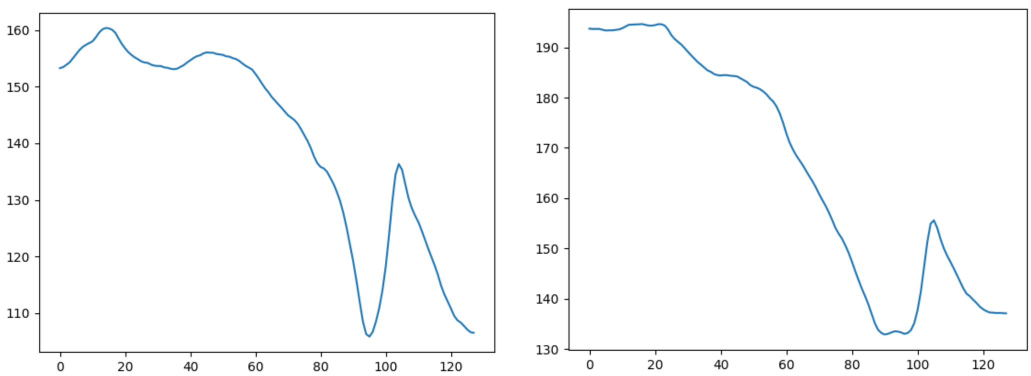

Figure 11 – Column plotting the mean values of the partitioned pictures allowed Figure 10 to identify the maximum points after the valley point.

Level 3 wavelet coefficients are shown using the "db6" mother wavelet. The map indicates the local maxima (Lm) and the strong valley (Sv) to help one better understand where the ROI limits are. This wavelet-based study considers variations in illumination and contrast, therefore enhancing feature extraction.

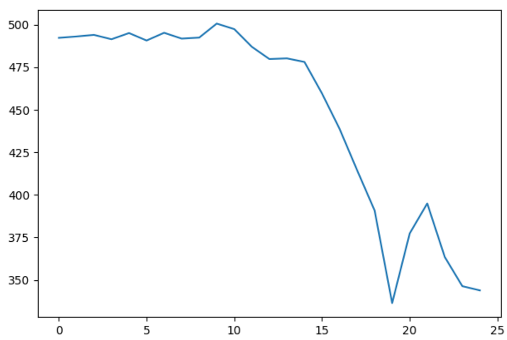

Figure 12 – Level 3 wavelet coefficients utilising the "db6" mother wavelet.

Figure 13 displays the last ROI obtained using wavelet-based transformations and scaling guidelines. Focused on the space between the knee joints, the median-filtered image is neat, clear. The ROI gets rid of the unnecessary components and maintains the key elements required for KL grading.

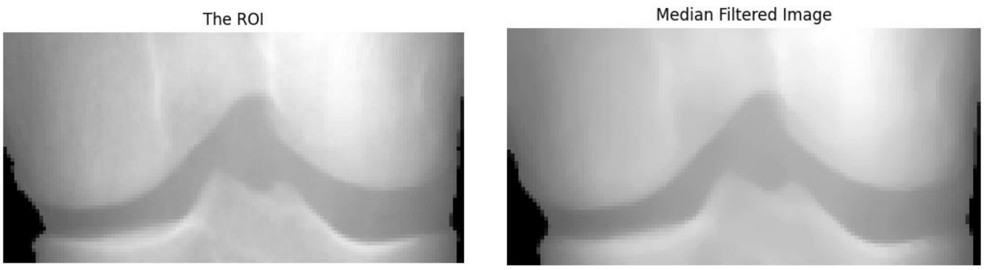

Figure 13 –Region of interest (ROI) extracted following the last crop operation. Picture using a median filter after ROI.

Figure 14 shows the binarized image of the ROI, therefore illustrating the difference between the knees. Accurate measurement of the joint gap made possible by the distinct separation of black and white sections prepares the image for feature extraction and categorisation. It is abundantly evident from the binarized output how crucial correct segmentation is for obtaining decent classification accuracy.

Figure 14 –The distance between the knees is plainly visible in this binarized picture.

6. Results and Discussion

Figure 15 shows the original knee X-rays along with their associated split areas of interest (ROIs). For each Kellgren and Lawrence (KL) grade—from Grade 0 (Normal) to Grade 4 (Severe Osteoarthritis)—there is one. Using noisy, non-looking-like X-ray images, this image illustrates how well the proposed system performs in producing meaningful ROIs. The top row displays the original photos, therefore illustrating the range of quality in the collection. Accurate tagging is very difficult when photos have poor contrast, uneven illumination, or noise. The ROIs split according to the pre-processing phase of the framework shown in the following rows. These split images help one to clearly distinguish the knee joint region from other areas not required, therefore facilitating the identification of crucial diagnostic elements. The separated ROIs grow smaller when the KL grade increases between the upper and lower knee bones. The knee is healthy for Grade 0 as the joint gap is large and readily evident. Given the shrinking difference for Grade 1, osteoarthritis is most probable. The gaps narrow and the hard tissues surrounding grades 2 and 3 change texture in a manner you can perceive. By Grade 4, the difference is almost closed and osteophyte development and inflammation abound. This image illustrates how the framework can extract ROIs displaying significant information for grading OA, including the diameter of the joint gap and the appearance of the tissue. More accurate feature extraction and classification are opened by the obvious variation in split ROIs between grades, which also reveals the dependability of the technique.

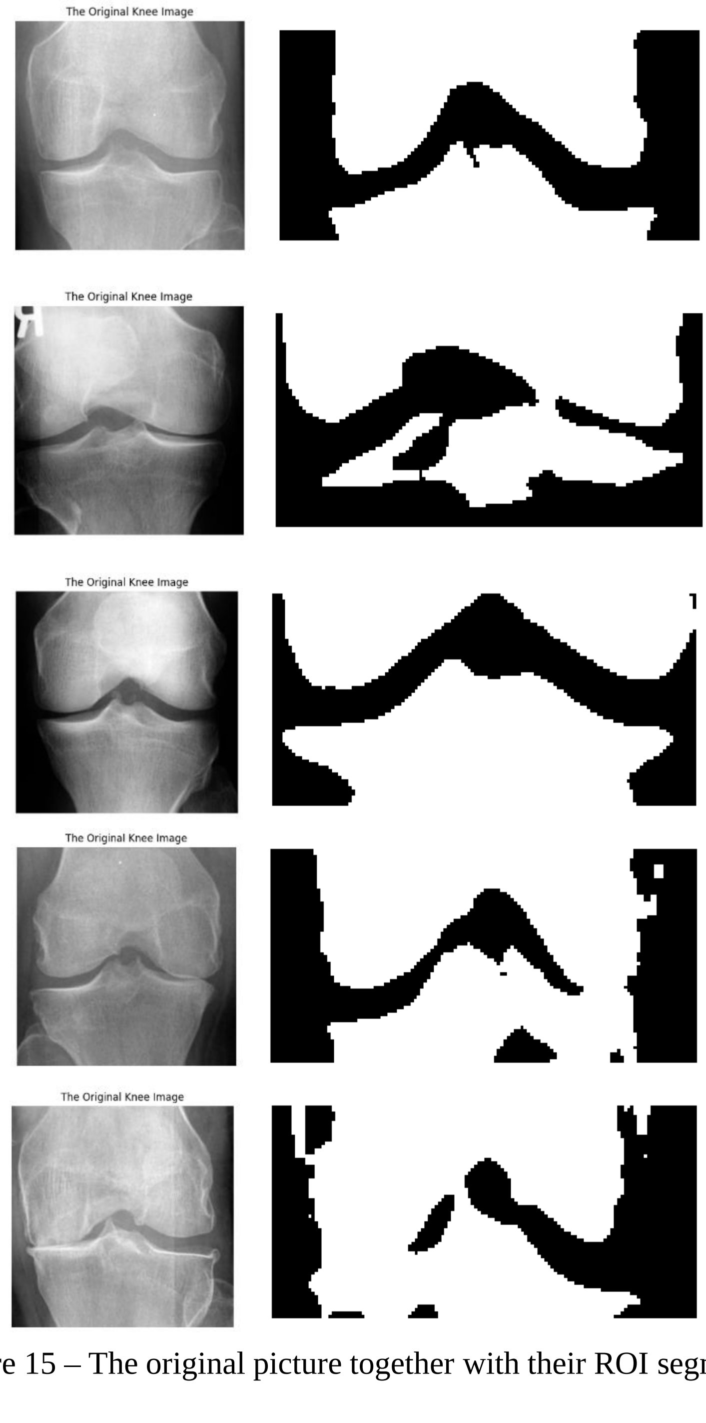

Figure 15 – The original picture together with their ROI segments.

7. Conclusion

Typical issues in medical imaging include noise, poor contrast, and unequal illumination. The proposed approach for pre-processing knee X-ray images performs really well in addressing these issues. The system finds the area of interest (ROI) for evaluating knee osteoarthritis (OA) by means of a planned approach including Gaussian blurring, thresholding, cropping (both vertically and horizontally), downsizing, and sophisticated statistical and wavelet-based feature tuning. This makes it simple to split the knee joint region into unambiguous portions displaying significant information like the joint gap and hard tissues surrounding it, which are required for proper scoring using the Kellgren and Lawrence (KL) approach. From Grade 0 (healthy knees) to Grade 4 (severe osteoarthritis), the test findings demonstrate the framework can manage variations in image quality across all five KL classes. The segmented ROI removes non-essential regions and preserves significant diagnostic traits, hence clarifying categorisation. For automated OA recognition, the framework's flexibility in changing to various image scenarios increases its generalisable value. The framework improves the classification characteristics and divides the ROI very well. Work in the future may concentrate on introducing contrast enhancement techniques to better manage conditions with very little light. Investigating more sophisticated noise removing filters that maintain edge information might also help to increase segmentation accuracy. At last, by ensuring first-rate pre-processing and segmentation, the recommended method lays a solid basis for automated OA identification. It is thus a significant contribution to the area of medical image processing as it makes subsequent operations like feature extraction and classification more understandable and more accurate.

Declaration of Interests: Authors have no conflicts of interest.

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