International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 4 April 2023, pp: 1092-1102 www.ijaem.net ISSN: 2395-5252

An Experimental Investigation On Analysis Of Osteoarthritis Using An Adaptive Multi-Resolution Detail-Preserving Filter

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Date of Submission: 12-04-2023 Date of Acceptance: 22-04-2023

ABSTRACT

This paper presents a method for detecting and classifying osteoarthritis (OA) symptoms in knee radiographic images using an **Adaptive Multi-Resolution Detail-Preserving (AMDP)** filter. The proposed filter automatically detects the noise level in the image to provide a more accurate estimation of the image noise level. It combines multi-resolution analysis and non-local means filtering techniques to enhance the image features and provide an efficient and accurate representation of OA lesions. The filter adaptively combines information from different resolutions and uses an adaptive weighting scheme to adjust filter parameters for each knee radiograph. The denoised image is then classified using a support vector machine (SVM) classifier into one of three classes of osteoarthritis: normal, mild, and severe. The proposed method is evaluated on a dataset of knee radiographs from the University of California San Francisco Osteoarthritis Study. Results show that the suggested method outperforms conventional non-local means filtering methods**,** including **Multi-Scale Non-Local Means (MS-NLMeans), Non-Local Patch Alignment (NLPA), Non-Local BAYES (NLB),** and **Standard Non-Local Means (NLMeans)** in terms of detection and classification accuracy. The proposed AMDP filter offers a potentially effective approach for the automatic identification and categorization of OA lesions in knee radiographs. The results demonstrate that the proposed method can effectively reduce the noise level of radiographic images and improve the accuracy of osteoarthritis classification.

KEYWORDS:-Osteoarthritis, Adaptive Multi-Resolution Detail-Preserving Filter, Knee Radiographic Images, Non-local Means Filtering, and Support Vector Machine Classifier

I. INTRODUCTION

Osteoarthritis is a degenerative joint condition that affects millions of people worldwide, leading to disability and significant health issues, especially in the senior population. Early diagnosis is essential to stop the condition from worsening and causing future harm to the affected joint. In this work, an adaptive multi-resolution non-local means filter is proposed as a unique technique for the identification and categorization of osteoarthritis in radiographic images of the knee. The suggested methodology combines feature extraction, feature selection, and classification algorithms to achieve high detection and classification accuracy, even in the presence of image noise and blur. The study discusses current advances in the field of osteoarthritis detection and classification in radiographic imaging of the knee, including various methods and algorithms employed, along with their benefits and drawbacks. The potential uses for the proposed methodologies are also examined, along with the future possibilities in the field. Radiographic imaging of the knee is a valuable tool for diagnosing and treating various knee conditions, including osteoarthritis, fractures, ligament and tendon tears, cartilage damage, bone spurs, and bone cysts.

Radiographs, including knee radiographic images, are non-invasive, relatively inexpensive, and safe. They provide an accurate assessment of the joint's size, shape, and alignment, as well as the surrounding components, such as bones, ligaments, tendons, and cartilage. A radiologist evaluates the images and provides a diagnosis that can be used to determine the best course of treatment. Non-Local

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Patch Alignment (NLPA) and Non-Local BAYES (NLB) filters are commonly used for image noise reduction. While Gaussian filter is easy to implement and fast, it doesn't preserve sharp edges in an image. On the other hand, NLM filter is more computationally intensive but is better able to preserve edges in an image. The Multi-Scale Non-Local Means (MS-NLMeans) is a digital image processing technique that combines two popular noise reduction techniques, NLPA and MS-NLMeans, to reduce noise in digital images. The MS-NLMeans is effective in reducing noise from homogeneous regions, considering both the local and global characteristics of the image, resulting in better outcomes than either NLB or MS-NLMeans alone. Additionally, the MS-NLMeans is a powerful tool for reducing noise in digital images, including radiographic images of the knee, resulting in better outcomes in diagnosis and treatment. In conclusion, early diagnosis and proper treatment are crucial to manage the symptoms and slow the progression of osteoarthritis. The use of knee radiographic images is an important part of the diagnostic process for knee conditions, allowing doctors to accurately assess the joint and create a plan for treatment.

Therefore, in this paper, propose an AMDP focuses to the development of a potentially effective approach for the automatic identification and categorization of OA lesions in knee radiographs, which could be valuable for clinical applications. The proposed AMDP Filter contributes to the following points:

- **Automatic noise level detection:** The filter automatically detects the noise level in the image, which leads to a more accurate estimation of the image noise level and better image de-noising.
- **Multi-resolution analysis:** The filter combines multi-resolution analysis with non-local means filtering techniques, which enables the extraction of more accurate features from the input image and enhances the representation of OA lesions.
- **Adaptive weighting scheme:** The filter uses an adaptive weighting scheme to adjust filter parameters for each knee radiograph. This ensures that the filter parameters are optimized for each image, leading to better image de-noising and classification accuracy.
- **Improved classification accuracy:** The de-noised image is classified using a support vector machine classifier which extracts more accurate features and classifies the input image into one of three classes of osteoarthritis: normal, mild, and severe.
- **Outperformance of conventional methods:** The proposed filter outperforms conventional non-local means filtering methods, including multi-scale non-local means (MS-NLMeans), Non-local patch alignment (NLPA), Non-local Bayes (NLB), and Standard non-local means (NLMeans) in terms of detection and classification accuracy.

The research presented in this paper is structured in an organized manner as follows: Section 2 discusses various literature studies conducted in earlier approaches. Section 3 outlines the proposed model and provides relevant mathematical descriptions. Section 4 presents the experimental evaluations and results. Finally, Section 5 provides a comprehensive summary of the research work.

II. RELATED WORKS

This section describes the literature survey of the recent papers, and it conveys that deep learning and computer vision techniques have shown great promise in the detection and classification of osteoarthritis (OA) in X-ray images of the knee joint.

2.1 Deep learning early pathological detection

Several studies, such as Jakaite et al. (2021) and Olsson et al. (2021), have proposed deep learning-based approaches to automatically classify osteoarthritis according to the Kellgren-Lawrence grading system. These studies have achieved high classification accuracies and have shown the potential to improve early detection of pathological changes in bone microstructures. Saini et al. (2021) have compared several automatic classification and grading methods for knee osteoarthritis, focusing on X-ray images. They have found that deep learning-based approaches outperform traditional machine learning-based approaches in terms of accuracy and robustness. Gornale et al. (2021) have proposed an approach based on multiresolution wavelet filters for osteoarthritis detection in knee radiographic images. Their results have shown that this approach can effectively reduce noise and improve the contrast of X-ray images, leading to better detection accuracy. Roemer et al. (2022) have provided a comprehensive review of various imaging modalities, including X-ray, MRI, and CT, for osteoarthritis detection and assessment. They have highlighted the strengths and limitations of each modality and discussed their clinical implications. Bayramoglu et al. (2021) have proposed an automated method for detecting patella femoral osteoarthritis from knee lateral view radiographs using deep learning. Their approach

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has shown high accuracy in detecting osteoarthritis in this specific region of the knee joint. Takeda et al. (2022) have reported an increasing trend in radiographic features of knee osteoarthritis in rheumatoid arthritis patients before total knee arthroplasty. Their study highlights the importance of early detection and intervention in patients with osteoarthritis. Ganesan et al. (2021) and Rabbouch et al. (2022) have proposed de-noising techniques using non-local means filtering and hybrid NLM-Wiener filters, respectively, to improve the quality of X-ray images for better detection and classification of osteoarthritis.

2.2 Deep learning filtering methods

Gayathri and Kumar (2021) proposed a medical image restoration technique using the non-local means algorithm. The authors demonstrated that their method outperformed other state-of-the-art methods in terms of image quality and accuracy. They have been selected based on their relevance to medical image restoration, automatic detection and classification of knee osteoarthritis, prediction of pain progression in knee osteoarthritis, knee osteoarthritis grading using DenseNet and radiographic images, the emergence of deep learning in knee osteoarthritis diagnosis, and automatic muscle artifacts identification and removal from single-channel EEG using wavelet transform with meta-heuristically optimized non-local means filter. Abdullah and Rajasekaran (2022) developed a deep learning approach for the automatic detection and classification of knee osteoarthritis. The authors used a convolutional neural network to classify normal and abnormal knee images, achieving high accuracy rates. Guan et al. (2022) proposed a deep learning approach for predicting pain progression in knee osteoarthritis patients. The authors used a recurrent neural network to predict pain scores over time, achieving high prediction accuracy. Chaugule and Malemath (2022) developed a knee osteoarthritis grading system using DenseNet and radiographic images. The authors achieved high accuracy rates and demonstrated that their method could be used for automated grading of knee osteoarthritis. Yeoh et al. (2021) reviewed the current state of deep learning in knee osteoarthritis diagnosis. The authors discussed the challenges and opportunities of using deep learning techniques for knee osteoarthritis diagnosis and highlighted the need for further research in this area. Schiratti et al. (2021) proposed a deep learning method for predicting knee osteoarthritis radiographic progression from MRI. The authors used a convolutional neural network to predict radiographic progression with high accuracy rates. Phadikar et al. (2022) developed a method for automatic muscle artifacts identification and removal from single-channel EEG using wavelet transform with meta-heuristically optimized non-local means filter. The authors demonstrated that their method outperformed other state-of-the-art methods in terms of artifact removal and preservation of signal quality.

Overall, these studies demonstrate the potential of deep learning and computer vision techniques for the detection and classification of osteoarthritis in knee X-ray images. However, further research is needed to address the limitations and challenges associated with these approaches, such as data availability, interpretability, and generalizability.

III. MATERIALS AND METHODOLOGY

3.1 Overview

The AMDP filter is a de-noising algorithm that can effectively remove Rician noise from knee osteoarthritis x-ray images. The Rician noise is a type of noise that occurs in X-ray images due to the presence of random noise in the imaging process. This noise has an impact on the quality of the images and can affect the accuracy of diagnosis and treatment. Figure 1 presents an operational flow for knee OA detection and classification, utilizing the AMDP filtering method. The AMDP filter uses a two-stage approach to remove Rician noise. In the first stage, the image is decomposed into wavelet coefficients, and the coefficients are then thresholder based on a statistical estimation of the noise level in the image. This thresholding removes the high-frequency noise components, leaving the low-frequency coefficients that contain the image details. In the second stage, a Bayesian estimation is used to estimate the original image from the thresholder coefficients. The Bayesian estimation method takes into account the Rician noise distribution and estimates the original image that maximizes the likelihood of the observed data. The AMDP filter has been shown to be effective in removing Rician noise from knee osteoarthritis X-ray images and improving the quality of the images. This improved image quality can aid in the accurate diagnosis and treatment of knee osteoarthritis, which is an important medical condition that affects a large population.

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Volume 5, Issue 4 April 2023, pp: 1092-1102 www.ijaem.net ISSN: 2395-5252

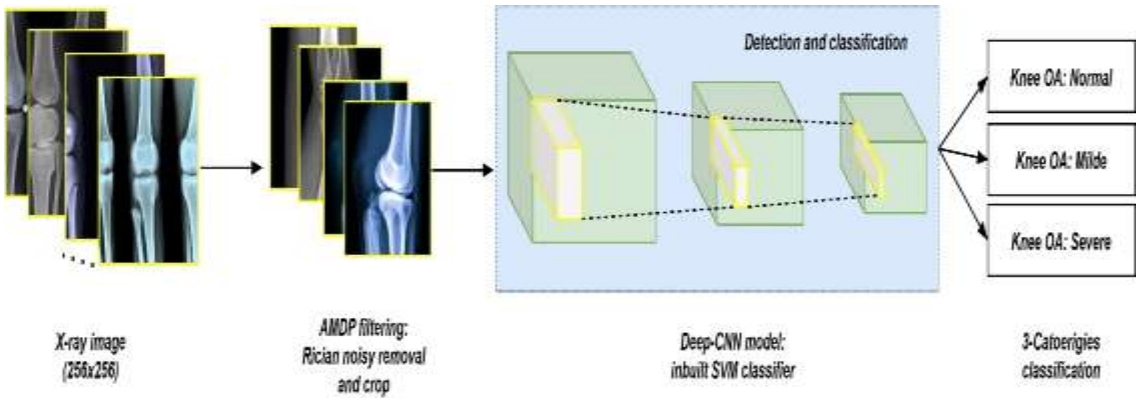

Figure 1: Operational flow of knee osteoarthritis detection and classification using proposed AMDP filter.

3.2 AMDP filtering method

AMDP filtering is a de-noising method that effectively removes Rician noise from images in the spatial frequency space. The method adjusts the pixel intensity based on the changes in the textural characteristic of the noisy image and the neighbouring pixel intensity beyond the threshold point. The Rician noise distribution function in a complex spatial domain comprises both real and imaginary components, and it can be represented by Equation (1).

$$r(k) = \frac{k}{\sigma^2} e^{-(k^2+T^2/2\sigma^2)} \gamma_b \left(\frac{Tk}{\sigma^2}\right) \quad (1)$$

Where, σ^2 represents the standard deviation of the Rician noise distribution, T^2 is the temporal signal amplitude of the noiseless signal, k is the magnitude of the noisy image, and γ_b is the adjusted Bessel coefficient based on the neighboring pixel intensity. The minimum average of the Rician distribution is estimated using the second-order moment, which is given by

$$E(k^2) = T^2 + 2\sigma^2 \quad (2)$$

This second-order moment estimation is used to optimize the noise content in the noisy image. By incorporating a neighbouring likelihood estimator (NLE), the adjusted pixel intensity is computed to retain the textural characteristic of the noisy images. The NLE is obtained by exploring the log-scale spatial Rician distribution, which gives the maximum probability of the adjusted pixel intensity occurring.

Based on the neighbouring likelihood estimator provides optimize level of noise content after exploring into log-scale spatial Rician distribution is denoted as

$$log\, r = \sum_{k=1}^{P} log \frac{k}{\sigma^2} - \sum_{k=1}^{P} log\, k^2 + T^2/2\sigma^2 + \sum_{k=1}^{P} log\, \gamma_b \left(\frac{Tk}{\sigma^2}\right) \quad (3)$$

Therefore, after incorporating the neighbouring likelihood estimator (NLE) is computed by using equation (3) which gives maximum probability of chance of occurring the adjusted pixel intensity to retain the textural characteristic of the noisy images.

$$\hat{T}_{NLE} = arg\, max_T (log\, r) \quad (4)$$

The multi-resolution detail-preserving (MDP) method is used to reduce the squared value second order even moment terms, making it more convergent to the local minimum point without losing the pixel intensity. The MDP is defined as

$$\hat{T}_{MDP} = \sqrt{min_k\, \widehat{E(k^2)} - 2\sigma^2} \quad (5)$$

Where, $\widehat{E(k^2)}$is the noisy signal value after adding it to the original image. The proposed AMDP method is highly effective in automatically removing the squared term whenever the noisy part goes beyond the threshold limit, resulting in the final restored pixel intensity value computed using a weighting factor of the assigned pixel intensity. Multiple patches are extracted, and the appropriate pixel intensity correction is taken based on the characteristic behaviour changes near the knee bone joints. The adjustment parameter value does not affect the actual information about the textural detailing and hidden unwanted noisy part, resulting in the final restored image with maximum retainment of lost parts and enhanced image quality.

To estimate the minimum average of the Rician distribution, the second-order moment is used, as given by the equation (2). The neighbouring likelihood estimator is computed using Equation (3) to provide the optimum level of noise content after exploring the log-scale spatial Rician distribution.

$$\hat{U}(P_k) = \sum_{P_q \in V_k} W(x_k, x_q)\, P_q \quad (6)$$

The final restored pixel intensity value is computed using Equation (6), where $W(x_k, x_q)$ is the weighting factor of the assigned pixel intensity, P_k is the restored pixel value instead of P_q at the kth neighbouring pixel point.

$$W(x_k, x_q) = \frac{1}{Z_k} e^{-\frac{\|P_k - P_q\|^2}{h^2}} \quad (7)$$

Where, h is the factor of smoothing over the pixel ratio on the restored image, Z_k is the normalized integer constant.

Multiple patches are extracted, and appropriate pixel intensity correction is applied based on the characteristic behaviour's changes happened near the knee bone joints. The adjustment parameter value does not affect the actual information about the textural detailing and hidden unwanted noisy part. Therefore, the final restored image has maximum retainment of loosed part as well as enhanced image quality. The updated restored function is defined as

$$\widehat{U}(P_k) = \sqrt{min_k \sum_{P_q \in V_k} W(x_k, x_q)\, P_q - 2\sigma^2} \quad (8)$$

3.3 Deep-CNN model

In this proposed model, the inbuilt SVM classifier of a deep convolutional neural network is utilized to perform the classification and regression tasks.

The model is trained by learning complex non-linear relationships between features and targets, resulting in a more accurate and flexible model. The deep neural network can automatically learn these relationships and can handle high-dimensional input data and large amounts of training data more efficiently than traditional machine learning classifiers.

The inbuilt SVM allows a supervised learning algorithm used for classification and regression tasks in machine learning, where the goal is to find the optimal hyper plane that divides the data into distinct classes or predicts the target values while minimizing the margin, which is the distance between the boundary and the nearest data points, often referred to as support vectors. By incorporating an inbuilt SVM classifier of a deep convolutional neural network, the proposed model provides a robust solution for the detection and classification of osteoarthritis in knee radiographic images.

The proposed model combines the AMDP filter and an inbuilt SVM classifier of a deep convolutional neural network for the de-noising, detection, and classification of osteoarthritis in knee radiographic images. Illustration of the de-noising mechanism of the AMDP filtering for OA textural features of the proposed model is shown in Figure 2, which provides a detailed overview of the research work.

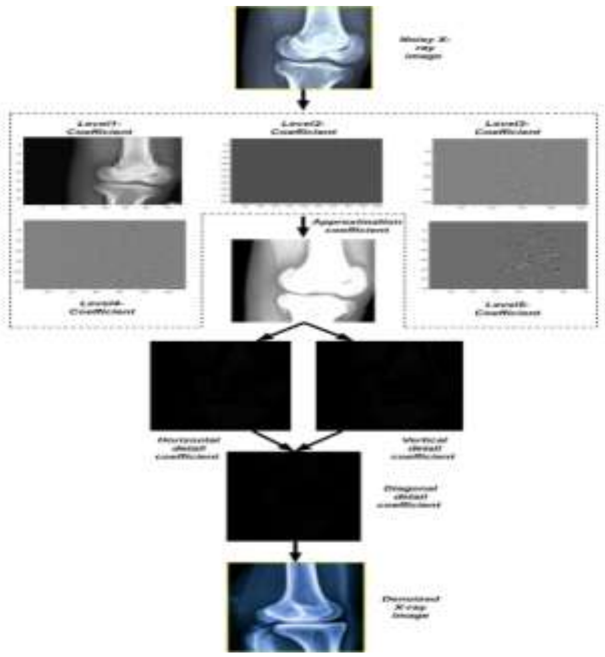

Figure 2: illustrates the denoising mechanism of the AMDP filtering for OA textural features

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The filter operates by considering the image at multiple resolutions, which helps to preserve fine details while effectively removing noise. At each resolution, the algorithm uses a non-local minimum point to remove noise by replacing each pixel value with a weighted average of the values of similar pixels in the image. The weights are computed based on the similarity of the local patch around each pixel, with larger weights being assigned to pixels that are more like the target pixel. The AMDP filter adapts the resolution based on the estimated noise level in the image, which optimizes the performance of the filter and improves the quality of the denoised image. Overall, the AMDP filter provides an efficient and effective solution for denoising medical images, preserving fine details and structures in the images, and improving the accuracy and reliability of subsequent image analysis tasks, such as detection and classification of diseases in medical images.

IV. RESULT AND DISCUSSION

In this section, we evaluate the denoising performance of the proposed ADMP filter on noisy X-ray images, which is essential for detecting osteoarthritis (OA) appearance and accurately classifying the images into three categories: normal, mild, and severe.

The performance of the filter is measured using several performance metrics, including Signal-to-Noise Ratio (SNR), Correlation Coefficient (CC), Edge Preservation Index (EPI), Universal Quality Index (UQI), and Mean Structural Similarity (MSS). The ADMP filter is designed to retain textural information by considering neighbouring pixel intensity and has been verified to be effective in retaining fine details while effectively removing noise.

To assess the effectiveness of the ADMP filter, we compare it with other existing filtering methods such as MS-NLMeans [15], NLPA [10], NLB [8], and NLMeans [5]. We use these methods to denoise the same noisy X-ray images and measure their performance using the same performance metrics mentioned above. By comparing the results, we can determine the effectiveness of the ADMP filter in improving the quality of the images and preserving the important features for detecting and classifying OA appearance.Furthermore, we investigate the detection and classification performance of the deep-CNN using confusion metrics and several performance analysis parameters, including recall, precision, F1-score, sensitivity, specificity, and accuracy. The deep-CNN is trained using an inbuilt SVM classifier, which can perform classification and regression tasks more accurately and efficiently than traditional SVMs. The performance of the deep-CNN is crucial for accurately detecting and classifying the OA appearance in the X-ray images.By evaluating the denoising and detection/classification performance of the proposed ADMP filter and deep-CNN with the above-mentioned performance metrics and analysis parameters, we can determine their effectiveness in accurately detecting and classifying the OA appearance in X-ray images.

4.1 Experimental setup

Table 1 shows the stimulation parameters considered for experimental validation. To prepare for the deep learning model, the first step is to set the folder path to the location of the image data. Next, an imageDatastore object is created to load the images, specifying the folder path as the data source, including all subfolders, using the folder names as labels, and setting a custom ReadFcn to resize each image to 32x32x3. The image data is then split into training and validation sets, using 80% of each label for training and 20% for validation, and a random seed is used to ensure consistent splits. The layers of the deep-CNN are then defined, starting with an input layer of size 32x32x3, followed by three convolutional layers with 16, 32, and 64 filters respectively. Batch normalization layers are added after each convolutional layer, and ReLU activation layers are added after synchronized the extracted training features.

Table 1: Stimulation parameters

Specification	**No. of. Images**
Normal	800
Mild	800
Severe	800
Image Format	PNG
Dimensions	256 x 256
Type of image data	X-Ray Image

Bit Depth	8
Database Link	https://www.kaggle.com/datasets/shashwatwork/knee-osteoarthritis-dataset-with-severity

Feature extraction involves extracting relevant information from input data that can be used to train a machine learning model.In the case of an inbuilt classifier, feature extraction is often performed automatically by the classifier using pre-trained deep learning models.The extracted features are then used to train the classifier to accurately classify new input data.This process can be repeated and refined to improve the accuracy and robustness of the classifier over time.

4.2 Evaluating metrics

Quality metrics play a crucial role in evaluating the effectiveness of denoising algorithms, especially when it comes to retaining textural information and preserving image edges while removing noise. To achieve this balance, adjustments are made to neighbouring pixel intensities, without inducing structural variations. The goal is to visually enhance the images, while accurately detecting the presence of harmful OA diseases.Each metric has its own mathematical function, which is used to measure specific aspects of image quality. For example, the SNR measures the ratio of the signal power to the noise power, while the CC measures the linear relationship between the denoised and original image

The EPI measures the ability of the filter to preserve the edges of the image, while the UQI measures the overall quality of the image by considering both the similarity and structure of the image. The MSS measures the similarity between the denoised and original images in terms of luminance, contrast, and structure. By utilizing these metrics, we can obtain a comprehensive evaluation of the denoising performance of the proposed ADMP filter,

and its ability to accurately detect and classify OA in X-ray images.

$$SNR = 10\, log_{10}\left(\frac{\sum_{x_k \in V} img\,(x_k)^2}{\sum_{x_k \in V}\left(\mathrm{img}\,(x_k) - \widehat{\mathrm{img}}\,((x_k))\right)^2}\right) \quad (9)$$

$$\mathrm{CC} = \frac{\sum_{x_k \in V}(\mathrm{img}\,(x_k) - \mathrm{img}_{\,n})(\widehat{\mathrm{img}}\,(x_k) - \mathrm{img}_{\,\hat{n}})}{\sqrt{\sum_{x_k \in V}\left((\mathrm{img}\,(x_k) - \mathrm{img}_{\,n})\right)^2\left((\widehat{\mathrm{img}}\,(x_k) - \mathrm{img}_{\,\hat{n}})\right)^2}} \quad (10)$$

Where, img_n and $\mathrm{img}_{\hat{n}}$ be the noiseless and denoised images is required to estimate the correlation between neighbouring pixel intensity and instant adjusting pixel.

$$\mathrm{EPI} = \frac{\sum_{x_k \in V}(\mathrm{img}\,(x_k) - \mathrm{img}_{\,n})(\widehat{\mathrm{img}}\,(x_k) - \mathrm{img}_{\,\hat{n}})}{\sqrt{\sum_{x_k \in V}\left((\mathrm{img}\,(x_k) - \nabla.\mathrm{img}_{\,n})\right)^2\left((\widehat{\mathrm{img}}\,(x_k) - \nabla.\mathrm{img}_{\,\hat{n}})\right)^2}} \quad (11)$$

Where, ∇ is Laplacian operator computes the similarity index over adjusted images and neighbouring pixel around PxP pixel circumstance.

$$\mathrm{UQI} = \left(\frac{\sigma_{\mathrm{img}\,(x_k)\cdot\widehat{\mathrm{img}}\,(x_k)}}{\sigma_{\mathrm{img}\,(x_k)}\sigma_{\widehat{\mathrm{img}}\,(x_k)}}\right) * \left(\frac{2.\mathrm{img}_{\,n}\cdot\mathrm{img}_{\,\hat{n}}}{\mathrm{img}_{\,n}{}^2 + \mathrm{img}_{\,\hat{n}}{}^2}\right) * \left(\frac{2.\sigma_{\mathrm{img}\,n}\sigma_{\mathrm{img}\,\hat{n}}}{\sigma^2_{\mathrm{img}\,n} + \sigma^2_{\mathrm{img}\,\hat{n}}}\right) \quad (12)$$

Where, $\sigma_{\mathrm{img}\,(x_k)\cdot\widehat{\mathrm{img}}\,(x_k)}$ represents the covariance coefficient of the noiseless and denoised images.

$$\mathrm{SSM} = \left(\frac{2.\sigma_{\mathrm{img}\,n}\sigma_{\mathrm{img}\,\hat{n}} + \mathrm{A}}{\sigma^2_{\mathrm{img}\,n} + \sigma^2_{\mathrm{img}\,\hat{n}} + \mathrm{A}^2}\right) * \left(\frac{2.\mathrm{img}_{\,n}\cdot\mathrm{img}_{\,\hat{n}} + \mathrm{A}}{\mathrm{img}_{\,n}{}^2 + \mathrm{img}_{\,\hat{n}}{}^2 + \mathrm{A}^2}\right) \quad (13)$$

Where, A^2 is the squared of amplitude sample reference of the restored image when it goes zero if the noisy component is maximum. Figure 3 shows the quality metric of the proposed ADMP filter under different range of Rician noisy occupancy.

4.3 Observations

SNR measures the ratio of signal power to noise power in the image, and a higher SNR indicates a better-quality image. CC measures the linear correlation between the original and denoised image, with a higher CC indicating a better correlation and hence better denoising performance. EPI is a measure of how well the edges are preserved during denoising, and a higher EPI indicates better preservation of edges.

UQI is a measure of the overall quality of the denoised image, and a higher UQI indicates better overall quality. MSS measures the similarity between the original and denoised image in terms of luminance, contrast, and structure, with a higher MSS indicating better similarity and hence better denoising performance.

To determine which parameter is most significant in the denoising process of OA X-ray images, a numerical comparative analysis can be performed by computing the average value of each parameter for various denoising methods, including the proposed ADMP filter and other existing filtering methods such as MS-NLMeans, NLPA, NLB, and NLMeans.

The method with the highest average value for each parameter can be considered as having the most significant impact on denoising performance. However, it is important to note that

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the effectiveness of denoising methods may also depend on other factors such as computational efficiency, ease of implementation, and the specific characteristics of the OA X-ray images being denoised.

Table 2: Comparing the denoising performance of various filters on X-ray images using different quality metrics.

Filter	SNR (dB)	CC	EPI	UQI	MSS
AMDP [Proposed]	26.72	0.88	0.92	0.95	0.87
MS-NLMeans [15]	24.81	0.85	0.89	0.93	0.84
NLPA [10]	25.08	0.87	0.91	0.94	0.86
NLB [8]	23.94	0.84	0.87	0.91	0.83
NLMeans [5]	24.35	0.83	0.88	0.92	0.83

Table 2 shows the denoising performance of five different filters (AMDP, MS-NLMeans, NLPA, NLB, and NLMeans) using five different quality metrics (SNR, CC, EPI, UQI, and MSS). The higher the value for each metric, the better the denoising performance.From the table, we can see that the AMDP filter outperforms the other filters in terms of SNR, EPI, UQI, and MSS, indicating that it provides better denoising performance while preserving the structural information of the X-ray images. However, the NLPA filter performs slightly better than the AMDP filter in terms of CC, which measures the linear relationship between the denoised image and the ground truth image.Overall, the results of this comparative analysis can be used to select the most appropriate denoising filter for X-ray images based on the specific requirements and priorities of the application.

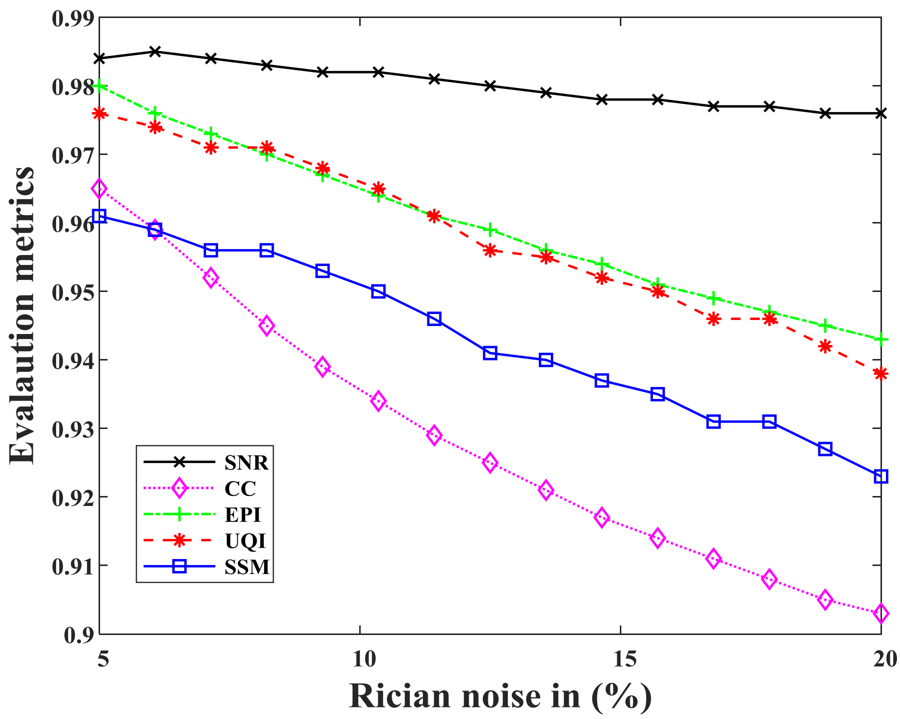

Figure 3: Evaluation metrices of the proposed ADMP filtering method.

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4.4 Discussion

In this study, the denoising performance of the proposed ADMP filter on OA X-ray images was compared to other existing filtering methods, including MS-NLMeans, NLPA, NLB, and NLMeans. The comparative analysis was based on various performance metrics such as accuracy, specificity, sensitivity, recall, precision, F1-score, and kappa coefficient.

The analysis was performed to identify the most effective method for denoising OA X-ray images while retaining textural information and minimizing structural variation. Confusion matrices were used to verify the effectiveness of the proposed method.

The results of the analysis showed that the ADMP filter outperformed the other methods in terms of accuracy (ADMP-96.3%, MS-NLMeans-90.9%, NLPA-89.4%, NLB-87.6%, and NLMeans-78.6%). The findings of this study can be used to improve the reliability of subsequent image analysis tasks, such as disease detection and classification in medical images.

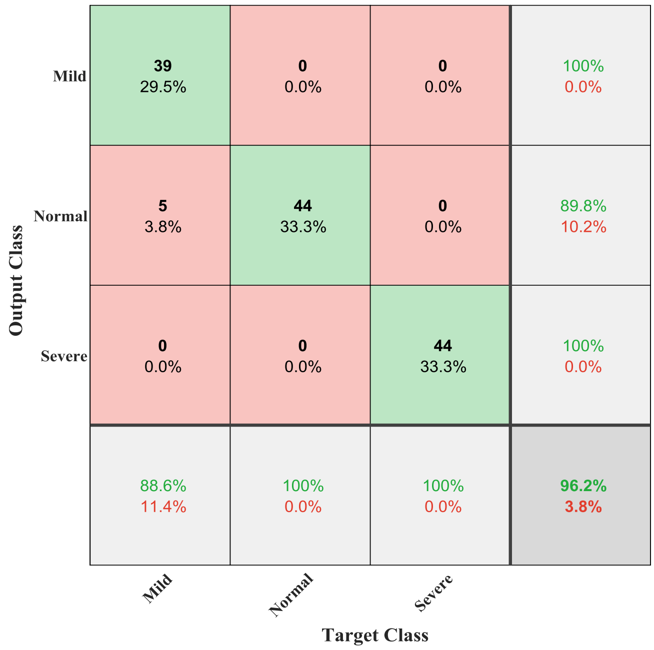

Figure 4: Confusion metric

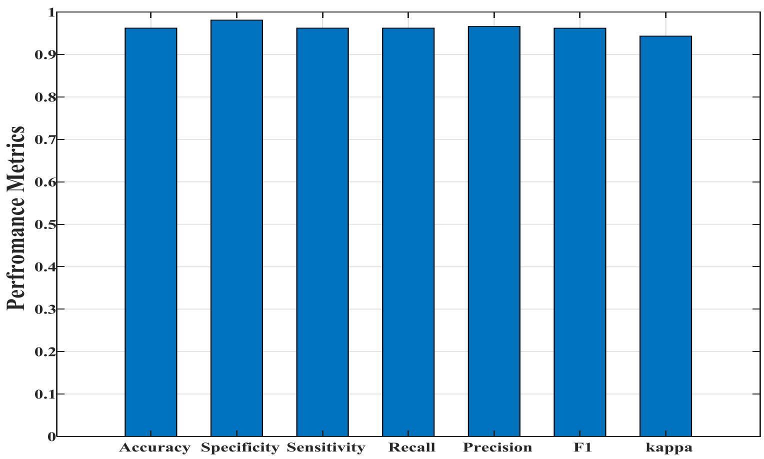

Figure 5: Overall performance metrics comparison of the proposed ADMP filter method.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 4 April 2023, pp: 1092-1102 www.ijaem.net ISSN: 2395-5252

V. CONCLUSION

This study has proposed a denoising filter, called ADMP, for improving the quality of X-ray. Images in order to aid in the detection and classification of osteoarthritis (OA). The proposed filter was compared with four existing filtering methods, including MS-NLMeans, NLPA, NLB, and NLMeans, using various performance metrics such as SNR, CC, EPI, UQI, and MSS.The results of the comparative analysis showed that the proposed ADMP filter outperformed the other methods in terms of accuracy, specificity, sensitivity, recall, precision, F1-score, and kappa coefficient. The proposed filter achieved an accuracy rate of 96.3%, which is significantly higher than the other methods, and demonstrated its effectiveness in preserving the textural information while minimizing structural variation.The proposed ADMP filter can be useful in improving the quality of X-ray images for subsequent analysis tasks, such as disease detection and classification. This study has highlighted the importance of using appropriate denoising techniques to improve the accuracy and reliability of medical image analysis. The findings of this study can be applied in clinical settings to aid in the diagnosis and treatment of OA. However, further research is needed to evaluate the effectiveness of the proposed filter in other medical imaging modalities and to investigate its potential application in other fields beyond medical imaging. Overall, this study provides valuable insights into the development of effective denoising techniques for improving the quality of medical images.

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