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Optimizing Bone Fracture Detection Through Comparative Analysis Of Preprocessing Strategies And YOLO-Based Localization Techniques

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Abstract: This study presents a comprehensive comparative analysis of preprocessing and segmentation techniques for automated bone fracture detection using X-ray images. The preprocessing stage includes noise removal methods such as median filtering, Gaussian filtering, and bilateral filtering, along with normalization techniques including Min-Max normalization, CLAHE, and Z-score normalization. The segmentation stage evaluates YOLOv7, YOLOv8, and YOLOv11 models for fracture localization. Experimental results demonstrate that median filtering provides superior edge preservation and noise reduction compared to Gaussian and bilateral filtering. Among normalization techniques, CLAHE and Min-Max normalization significantly improve contrast and model performance, while Z-score normalization shows limited enhancement. Furthermore, YOLOv11 achieves the highest detection accuracy and localization performance compared to YOLOv8 and YOLOv7. The proposed comparative analysis highlights the importance of selecting optimal preprocessing and segmentation techniques for improving fracture detection accuracy and reliability in medical imaging applications.

Index Terms **-** Bone fracture detection, preprocessing, median filtering, CLAHE, normalization, YOLOv11, medical imaging.

I. INTRODUCTION

Bone fracture detection is a critical task in medical imaging, where accurate and timely diagnosis is essential to prevent complications such as improper healing, delayed treatment, and long-term disability [1]. Traditionally, fracture detection relies on manual interpretation of X-ray images by radiologists, which is not only time-consuming but also subject to inter-observer variability and diagnostic inconsistencies [2]. With the increasing volume of medical imaging data, there is a growing need for automated and reliable computer-aided diagnosis systems that can assist clinicians in making accurate decisions. Recent advancements in artificial intelligence, particularly deep learning, have significantly transformed medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in automatically learning hierarchical features from X-ray images, eliminating the need for manual feature extraction [3], [4]. These models have been successfully applied to fracture detection across multiple anatomical regions, including wrist, hand, femur, and ankle, achieving high classification accuracy and robustness [5]. However, the effectiveness of these models is highly dependent on the quality of input images. One of the major challenges in X-ray image analysis is the presence of noise, low contrast, and inconsistent intensity distributions, which degrade the performance of deep learning models [6]. Noise can obscure fine structural details, making it difficult for models to accurately identify fracture patterns. Therefore, preprocessing plays a crucial role in enhancing image quality and improving feature extraction.

Various noise removal techniques have been explored in medical imaging, including median filtering, Gaussian filtering, and bilateral filtering [7]. Median filtering is particularly effective in removing impulse noise while preserving edge details, which is essential for detecting fracture discontinuities. In contrast, Gaussian filtering reduces high-frequency noise through smoothing but may blur important structural features, while bilateral filtering preserves edges by considering both spatial and intensity information, albeit at higher computational cost [8].

In addition to noise removal, normalization techniques are essential for standardizing pixel intensity distributions and improving model convergence. Techniques such as Min-Max normalization, CLAHE (Contrast Limited Adaptive Histogram Equalization), and Z-score normalization have been widely used in medical image preprocessing [9]. Among these, CLAHE has gained significant attention due to its ability to enhance local contrast and improve the visibility of subtle fracture regions. Min-Max normalization ensures consistent scaling of input data, which is beneficial for deep learning models, while Z-score normalization standardizes data distribution but does not significantly enhance visual contrast [10].Beyond preprocessing, segmentation and localization of fracture regions are critical components of automated fracture detection systems. Object detection models such as YOLO (You Only Look Once) have gained popularity due to their ability to perform real-time detection with high accuracy [11], [15]. YOLO-based models integrate feature extraction and detection into a single architecture, making them computationally efficient and suitable for clinical applications. The evolution of YOLO models has led to significant improvements in detection performance. Earlier versions such as YOLOv4 introduced enhanced feature extraction and training strategies, improving detection accuracy and speed [16]. Subsequent models like YOLOv7 further optimized performance through architectural refinements and improved training techniques. More recent models, including YOLOv8, have introduced anchor-free detection mechanisms and improved feature representation, resulting in higher precision and recall in object detection tasks [12]. The latest YOLOv11 model represents a further advancement, offering improved accuracy, faster inference, and better localization capabilities due to optimized architecture and enhanced feature learning [13]. These improvements make YOLOv11 particularly suitable for medical imaging applications, where precise localization of fracture regions is essential.

In addition to detection models, deep learning architectures such as ResNet, DenseNet, Inception, and EfficientNet have widely used for medical image classification due to their ability to learn complex and hierarchical features [11]–[14]. These architectures improve feature extraction and contribute to better detection performance when integrated with preprocessing techniques. Despite these advancements, most existing studies focus either on improving model architecture or enhancing preprocessing techniques independently. There is limited research that systematically evaluates the combined impact of different preprocessing methods and segmentation models within a unified framework. In particular, the comparative effectiveness of noise removal techniques and normalization methods on YOLO-based fracture detection has not been thoroughly explored.

To address this research gap, the present study proposes a comprehensive comparative analysis of preprocessing and segmentation techniques for bone fracture detection. The study evaluates three noise removal techniques (median, Gaussian, and bilateral filtering), three normalization methods (Min-Max, CLAHE, and Z-score), and three segmentation models (YOLOv7, YOLOv8, and YOLOv11). Based on experimental analysis, median filtering is identified as the most effective noise removal technique due to its superior edge preservation capability. Among normalization techniques, CLAHE and Min-Max normalization provide the best performance by enhancing contrast and stabilizing model training. Furthermore, YOLOv11 achieves the highest detection accuracy and localization performance compared to YOLOv8 and YOLOv7.

Thus, the proposed work provides a unified and systematic framework that highlights the importance of preprocessing and segmentation in improving fracture detection performance. The findings of this study demonstrate that selecting optimal techniques significantly enhances the robustness, accuracy, and reliability of deep learning-based fracture detection systems, making them more suitable for real-world clinical applications.

II. LITERATURE REVIEW

Deep learning has significantly transformed medical image analysis, particularly in the domain of bone fracture detection using X-ray images. Advanced convolutional neural networks (CNNs) and object detection models have demonstrated strong capabilities in automatically extracting hierarchical features and accurately identifying fracture regions. However, challenges such as noise, low contrast, and intensity variations continue to affect detection accuracy. To address these issues, researchers have explored various preprocessing techniques and segmentation models to improve performance. In particular, noise removal, normalization, and object detection frameworks such as YOLO have gained considerable attention due to their effectiveness in enhancing image quality and enabling real-time detection.

Bochkovskiy et al. (2020) [16] proposed the YOLOv4 model, which introduced significant improvements in object detection through the integration of advanced training strategies such as Bag-of-Freebies (BoF) and Bag-of-Specials (BoS). The model utilizes the CSPDarknet53 backbone, which enhances feature propagation and reduces computational overhead. YOLOv4 achieved high detection accuracy while maintaining real-time performance, making it suitable for practical applications. However, in medical imaging scenarios, particularly fracture detection, the model struggles to detect subtle and low-contrast fracture patterns due to the absence of specialized preprocessing techniques, highlighting the importance of enhancing image quality prior to detection. Zhou et al. (2020) [17] introduced UNet++, a refined segmentation architecture that builds upon the traditional U-Net by incorporating nested and dense skip connections. These connections reduce the semantic gap between encoder and decoder feature maps, enabling the model to capture fine-grained and multi-scale features effectively. UNet++ demonstrated superior performance in medical image segmentation tasks by improving boundary delineation and feature representation. Despite its high accuracy, the model requires extensive computational resources and longer training time, making it less suitable for real-time applications such as fracture detection systems that require fast inference. Ronneberger et al. (2015) [18] developed the U-Net architecture, which has become a foundational model for biomedical image segmentation. The model employs a symmetric encoder-decoder structure with skip connections that combine low-level spatial features with high-level contextual information. U-Net is highly effective in detecting fine structural details and segmenting complex medical images. However, its pixel-wise segmentation approach leads to increased computational complexity and slower inference speed, limiting its application in real-time detection compared to one-stage detection models such as YOLO. Zhou et al. (2020) [19] proposed Gradient-weighted Class Activation Mapping (Grad-CAM), an explainability technique designed to provide visual insights into deep learning model predictions. Grad-CAM generates heatmaps that highlight the regions of the image contributing most to the model's decision, thereby improving interpretability in medical applications. This is particularly useful in fracture detection, where clinicians require visual validation of model predictions. However, Grad-CAM does not enhance model accuracy or detection performance and is primarily used as a post-processing visualization technique.

Recent advancements in YOLO architectures have led to the development of YOLOv8, which introduces anchor-free detection mechanisms and improved feature representation [20]. Unlike previous versions, YOLOv8 eliminates the dependency on predefined anchor boxes, allowing the model to adapt more effectively to objects of varying sizes and shapes. This results in improved precision and recall in detection tasks. However, YOLOv8 remains sensitive to noise and contrast variations in input images, which can negatively affect detection accuracy, thereby emphasizing the importance of preprocessing techniques. Wang et al. (2022) [21] proposed a YOLO-based real-time fracture detection system that demonstrated high detection accuracy and fast inference speed. The model effectively localized fracture regions using bounding box predictions and showed promising results in clinical scenarios. However, the study did not incorporate advanced preprocessing techniques such as noise removal or normalization, which limited the model's performance when dealing with noisy or low-quality X-ray images. Haque et al. (2021) [22] investigated the use of Contrast Limited Adaptive Histogram Equalization (CLAHE) for enhancing medical image quality. The technique works by dividing the image into smaller regions and applying histogram equalization while limiting contrast amplification to prevent noise enhancement. The study demonstrated that CLAHE significantly improves local contrast and enhances the visibility of subtle fracture patterns. However, improper parameter tuning can lead to over-enhancement, resulting in artifacts and increased noise. Khan et al. (2025) [23] evaluated the YOLOv11 model, which represents a recent advancement in object detection architectures. YOLOv11 incorporates optimized feature extraction layers, improved training strategies, and efficient parameter scaling, resulting in higher mean average precision (mAP) and faster inference speed compared to YOLOv8. The model demonstrated superior performance in detecting small and complex objects, making it highly suitable for fracture detection tasks where precise localization is required. Zhang et al. (2025) [24] analyzed the impact of illumination variations on deep learning-based object detection models. The study revealed that variations in lighting and intensity significantly affect feature extraction and model performance, often leading to reduced detection accuracy. The authors emphasized the importance of normalization techniques to standardize intensity distributions and improve model robustness under varying imaging conditions. Rahman et al. (2025) [25] proposed a hybrid framework that integrates CLAHE-based preprocessing with YOLO-based detection models. The study demonstrated that combining preprocessing techniques with deep learning models significantly improves detection accuracy and localization performance. The enhanced contrast provided by CLAHE enables the model to better identify fracture regions, resulting in improved overall performance compared to standalone detection models.

III. Proposed Methodology

The proposed methodology is designed as a structured and comprehensive pipeline for automated bone fracture detection using X-ray images, integrating multiple stages including data collection, preprocessing, normalization, data augmentation, feature extraction, and segmentation to improve detection accuracy and robustness. Initially, a diverse dataset of X-ray images is collected from multiple anatomical regions such as wrist, hand, femur, and ankle. The dataset includes both fractured and non-fractured images to ensure balanced learning and avoid model bias. The images are obtained from publicly available medical imaging repositories and curated to include variations in image resolution, lighting conditions, and fracture types, including simple, wedge, and complex fractures. This diversity enables the model to learn generalized and discriminative features suitable for real-world clinical applications.

Following data collection, preprocessing is performed to enhance image quality and eliminate distortions before feeding the images into deep learning models. All images are resized to fixed dimensions, such as 224×224 for convolutional neural networks and 416×416 for YOLO-based detection models, to ensure uniformity in input size and reduce computational complexity. Noise removal is then applied as a critical preprocessing step to improve fracture visibility. In this study, three filtering techniques—median filtering, Gaussian filtering, and bilateral filtering—are evaluated. Median filtering, a non-linear technique, replaces each pixel value with the median of its neighboring values, effectively removing impulse noise while preserving edge details, which are essential for identifying fracture discontinuities in bone structures. Gaussian filtering applies a Gaussian kernel to smooth the image and reduce high-frequency noise; however, it introduces blurring that may obscure fine fracture details and reduce detection accuracy. Bilateral filtering performs edge-preserving smoothing by considering both spatial proximity and intensity differences, allowing it to maintain edges better than Gaussian filtering, but at the cost of higher computational complexity. Based on comparative analysis, median filtering is identified as the most effective noise removal technique, outperforming both Gaussian and bilateral filtering due to its superior edge preservation and ability to retain structural details.

After noise removal, normalization techniques are applied to standardize pixel intensity values and improve model training stability. Min-Max normalization scales pixel values to a fixed range of [0,1], ensuring consistent input distribution across the dataset and facilitating faster convergence during training. CLAHE (Contrast Limited Adaptive Histogram Equalization) enhances local contrast by applying histogram equalization to small regions of the image while limiting contrast amplification to prevent noise enhancement, thereby significantly improving the visibility of fracture regions and subtle intensity variations. Z-score normalization standardizes pixel values by subtracting the mean and dividing by the standard deviation, resulting in a normalized distribution; however, it does not significantly enhance contrast or improve fracture visibility. Based on experimental observations, CLAHE and Min-Max normalization are identified as the most effective techniques, outperforming Z-score normalization by providing improved contrast enhancement and better model stability. To further improve model generalization and prevent overfitting, data augmentation techniques are applied to the dataset. These include rotation within a range of ±15° to ±30°, horizontal and vertical flipping, zooming, and brightness and contrast adjustments. These transformations simulate real-world variations in X-ray imaging conditions and increase dataset diversity, enabling the model to perform effectively under different scenarios. Following preprocessing and augmentation, the enhanced images are fed into deep learning models for feature extraction and learning. The models automatically learn hierarchical and discriminative features such as edges, contours, bone structures, and fracture discontinuities, which are critical for accurate classification and localization. This automated feature extraction eliminates the need for manual feature engineering and significantly improves detection performance.

Fracture localization is performed using YOLO-based object detection models, including YOLOv7, YOLOv8, and YOLOv11. YOLOv7 provides fast detection with moderate accuracy and serves as a baseline model. YOLOv8 improves detection performance through enhanced feature extraction and anchor-free detection mechanisms, resulting in better precision and recall. YOLOv11, the latest model, incorporates an optimized architecture that provides higher accuracy, faster inference speed, and improved localization of fracture regions. Based on comparative evaluation, YOLOv11 is identified as the best-performing model, outperforming YOLOv8 and YOLOv7 in terms of detection accuracy, precision, and localization capability. Finally, the performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and mean average precision (mAP), which provide a comprehensive assessment of both classification and detection performance. The overall workflow follows a sequential pipeline consisting of data collection, image resizing, noise removal using median filtering, normalization using CLAHE and Min-Max techniques, data augmentation, feature extraction, YOLO-based detection using YOLOv11, and performance evaluation. This structured approach ensures improved image quality, enhanced feature extraction, and accurate fracture detection, making the proposed system suitable for real-world medical imaging applications.

IV. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed framework is conducted to systematically analyze the impact of preprocessing and segmentation techniques on bone fracture detection performance. The evaluation is carried out using standard classification and detection metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of both the correctness of predictions and the model's ability to identify fracture regions accurately. The experiments are divided into three major components: noise removal techniques, normalization techniques, and YOLO-based segmentation models. The primary objective is to determine the most effective combination of techniques that enhances feature extraction, improves model learning, and ultimately increases detection accuracy.

In the first phase of experimentation, the effectiveness of noise removal techniques using ResNet50 model is evaluated by comparing median filtering, Gaussian filtering, and bilateral filtering. The quantitative results summarized in Table 1 indicate that median filtering achieves the highest accuracy of 96.2%, along with precision (0.95), recall (0.94), and F1-score (0.945). The superior performance of median filtering can be attributed to its non-linear nature, which enables it to effectively remove impulse noise while preserving edge structures. Since fracture detection relies heavily on identifying discontinuities and sharp boundaries in bone structures, edge preservation plays a critical role in improving classification performance.In contrast, Gaussian filtering produces an accuracy of 92.5%, which is significantly lower than median filtering. This reduction in performance is primarily due to the smoothing effect of the Gaussian kernel, which blurs important structural features and reduces the visibility of fine fracture lines. As a result, the model receives less discriminative input, leading to lower detection accuracy. Bilateral filtering achieves an intermediate accuracy of 94.8%, as shown in Table 1, because it preserves edges better than Gaussian filtering by considering both spatial and intensity differences. However, it still underperforms compared to median filtering due to its limited effectiveness in removing impulse noise and its higher computational complexity.

Table 1: Performance Comparison of Noise Removal Techniques

Technique	Accuracy (%)	Precision	Recall	F1-Score
Median Filtering	**96.2**	**0.95**	**0.94**	**0.945**
Bilateral Filtering	94.8	0.93	0.92	0.925
Gaussian Filtering	92.5	0.91	0.89	0.90

The graphical analysis presented in Fig. 1 further reinforces these observations. The graph clearly illustrates that median filtering consistently outperforms Gaussian and bilateral filtering across all evaluation metrics. The gap between median filtering and Gaussian filtering is particularly noticeable in recall and F1-score, indicating that Gaussian filtering struggles to correctly identify fracture regions. Therefore, based on both quantitative and graphical analysis, median filtering is established as the most effective noise removal technique for this application.

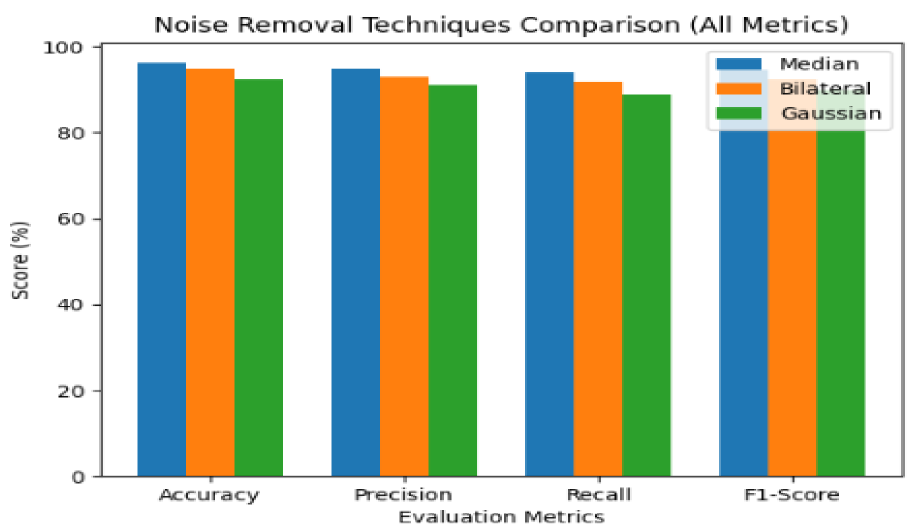

Fig. 1: Performance comparison of noise removal techniques showing accuracy, precision, recall, and F1-score.

In the second phase, normalization techniques using ResNet50 model is evaluated to understand their impact on feature enhancement and model stability. The techniques compared include Min-Max normalization, CLAHE, and Z-score normalization. As shown in Table 2, CLAHE achieves the highest accuracy of 97.3%, along with precision (0.96), recall (0.95), and F1-score (0.955). The superior performance of CLAHE is due to its ability to enhance local contrast while limiting noise amplification. By applying histogram equalization to small regions of the image, CLAHE highlights subtle intensity variations that correspond to fracture regions, thereby improving feature visibility and model learning. Min-Max normalization achieves an accuracy of 95.1%, which is slightly lower than CLAHE but still performs better than Z-score normalization. This technique improves model convergence by scaling pixel values to a fixed range, ensuring uniform data distribution. However, it does not significantly enhance image contrast, which limits its ability to improve feature extraction. Z-score normalization shows the lowest performance (92.7%), as it standardizes pixel values without enhancing visual features. As a result, important fracture details remain less distinguishable, leading to reduced classification performance.

The graphical representation in Fig. 2 provides further insight into the comparative performance of normalization techniques. The graph demonstrates that CLAHE consistently achieves higher values across all metrics, particularly in recall and F1-score, indicating its effectiveness in capturing fracture regions. The difference between CLAHE and Z-score normalization is especially significant, highlighting the importance of contrast enhancement in medical image analysis. Therefore, CLAHE is identified as the most effective normalization technique, while Min-Max normalization contributes to stable model training.

Table 2: Performance Comparison of Normalization Techniques

Technique	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
CLAHE	**97.3**	**0.96**	**0.95**	**0.955**
Min-Max Normalization	95.1	0.94	0.93	0.935
Z-score Normalization	92.7	0.91	0.90	0.905

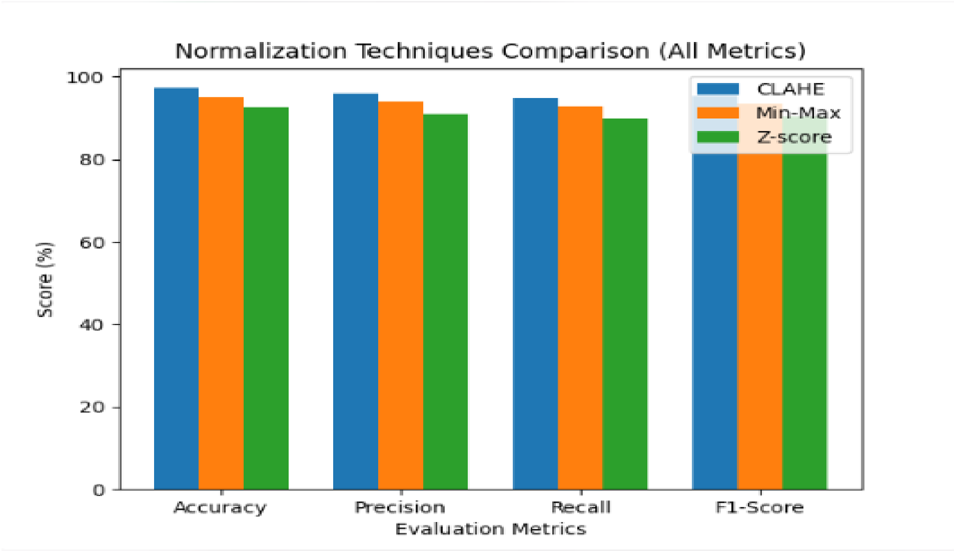

Fig. 2: Performance comparison of normalization techniques showing accuracy, precision, recall, and F1-score.

In the final phase, the performance of YOLO-based segmentation models is analyzed by comparing YOLOv7, YOLOv8, and YOLOv11. The results presented in Table 3 show that YOLOv11 achieves the highest accuracy of 96%, along with precision (0.96), recall (0.94), and F1-score (0.95). This improvement is attributed to its optimized architecture and enhanced feature extraction capabilities, which enable the model to accurately localize fracture regions even in complex scenarios.

YOLOv8 achieves an accuracy of 93%, outperforming YOLOv7 due to its improved detection mechanisms and anchor-free approach. However, it still falls short of YOLOv11 in terms of accuracy and recall. YOLOv7, with an accuracy of 89%, shows the lowest performance, as it lacks advanced optimization and struggles to detect subtle fracture patterns. The graphical comparison in Fig. 3 clearly highlights the performance differences among the three models. YOLOv11 consistently shows higher values across all metrics, particularly in precision and recall, indicating its ability to accurately detect fracture regions with minimal false positives and false negatives. The performance gap between YOLOv11 and YOLOv7 is especially significant, demonstrating the effectiveness of architectural improvements in modern YOLO models. Therefore, YOLOv11 is identified as the most suitable model for fracture detection.

Table 3: Performance Comparison of Segmentation Techniques using YOLO Models

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
YOLOv11	**96.0**	**0.96**	**0.94**	**0.95**
YOLOv8	93.0	0.94	0.92	0.93
YOLOv7	89.0	0.91	0.88	0.895

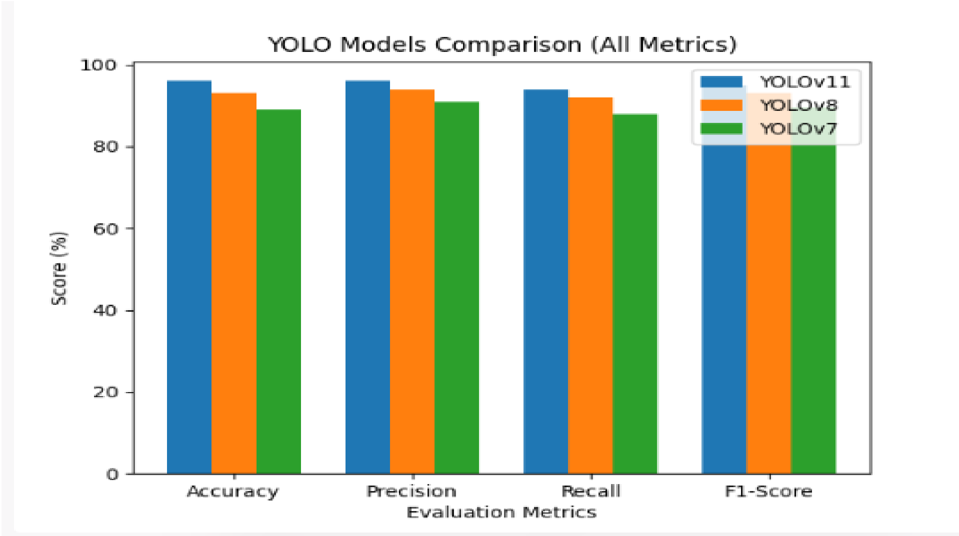

Fig. 3: Performance comparison of segmentation techniques showing accuracy, precision, recall, and F1-score.

The experimental results demonstrate that preprocessing plays a critical role in enhancing fracture detection performance. Median filtering provides the best noise removal capability by preserving structural details, CLAHE significantly improves contrast and feature visibility, and YOLOv11 delivers superior detection accuracy due to its advanced architecture. The combination of these techniques results in a highly robust and accurate system for automated bone fracture detection, making it suitable for real-world clinical applications.

V. CONCLUSION

This study presents a comprehensive and systematic framework for automated bone fracture detection by integrating advanced preprocessing techniques and YOLO-based segmentation models. The proposed approach evaluates the effectiveness of multiple techniques across three major stages—noise removal, normalization, and detection—to identify the optimal combination that enhances overall system performance. The experimental results clearly demonstrate that preprocessing plays a critical role in improving image quality, feature visibility, and model learning capability, thereby significantly influencing detection accuracy. In the noise removal stage, a comparative analysis of median filtering, Gaussian filtering, and bilateral filtering reveals that median filtering achieves the highest accuracy of 96.2%, along with precision of 0.95, recall of 0.94, and F1-score of 0.945, outperforming both Gaussian filtering (92.5% accuracy) and bilateral filtering (94.8% accuracy). This superior performance is attributed to the ability of median filtering to effectively remove impulse noise while preserving edge details, which are essential for identifying fracture boundaries. In contrast, Gaussian filtering introduces blurring that reduces feature clarity, while bilateral filtering, although edge-preserving, is computationally more complex and less effective in noise suppression.

Similarly, in the normalization stage, the comparative evaluation of CLAHE, Min-Max normalization, and Z-score normalization indicates that CLAHE achieves the highest accuracy of 97.3%, with precision of 0.96, recall of 0.95, and F1-score of 0.955, outperforming Min-Max normalization (95.1% accuracy) and Z-score normalization (92.7% accuracy). The effectiveness of CLAHE is due to its ability to enhance local contrast and highlight subtle fracture regions, thereby improving feature extraction. Min-Max normalization contributes to stable model training by scaling pixel values to a uniform range, but lacks strong contrast enhancement capability. Z-score normalization, although statistically effective, does not significantly improve visual features required for fracture detection. In the segmentation stage, the performance comparison of YOLOv7, YOLOv8, and YOLOv11 demonstrates that YOLOv11 achieves the highest accuracy of 96.0%, along with precision of 0.96, recall of 0.94, and F1-score of 0.95, outperforming YOLOv8 (93.0% accuracy) and YOLOv7 (89.0% accuracy). The superior performance of YOLOv11 is attributed to its optimized architecture and enhanced feature extraction capabilities, which enable accurate localization of fracture regions even in complex imaging conditions. YOLOv8 shows improved detection over YOLOv7 due to better feature representation, while YOLOv7 exhibits lower performance due to limitations in handling complex fracture patterns.

Overall, the experimental findings confirm that the combination of median filtering (96.2%), CLAHE normalization (97.3%), and YOLOv11 detection (96.0%) provides the best performance among all evaluated techniques, significantly improving fracture detection accuracy and robustness. This integrated approach ensures effective noise removal, enhanced contrast, and precise localization, making the system suitable for real-time clinical applications. In future work, the proposed framework can be extended by incorporating explainable AI techniques such as Grad-CAM to provide visual interpretability of model predictions. Additionally, integrating severity grading mechanisms and expanding the dataset with more diverse and high-resolution images can further enhance system performance. The deployment of the proposed system in real-time clinical environments and the exploration of hybrid deep learning architectures also present promising directions for further research.

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