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An Integrated Deep Learning Framework for Multi-Region Bone Fracture Detection with Severity Grading

Samanvaya K J
PG Scholar
Adichunchanagiri Institute of Technology, Chikkamagaluru, Karnataka, INDIA

Dr. Pushpa Ravikumar
Professor & Head
Adichunchanagiri Institute of Technology, Chikkamagaluru, Karnataka, INDIA

Arpitha C N
Assistant Professor
Adichunchanagiri Institute of Technology, Chikkamagaluru, Karnataka, INDIA

Abstract - Bone fracture detection is a critical task in orthopedic diagnosis that requires accurate and timely interpretation of radiographic images. Traditional manual analysis of X-ray images is time-consuming and often subject to inter-observer variability, especially in cases involving subtle or multi-region fractures. To address these challenges, this paper proposes a deep learning-based automated framework for multi-region bone fracture detection, localization, and severity grading. The proposed system integrates advanced Convolutional Neural Network (CNN) architectures, including ResNet50, DenseNet121, InceptionV3, and EfficientNetB3, for robust fracture classification. A YOLOv11-based detection model is employed for real-time localization and segmentation of fracture regions, enabling precise identification of affected areas. Furthermore, Grad-CAM is incorporated to provide explainable visualizations and assist in severity grading by highlighting fracture-relevant regions. The preprocessing pipeline includes normalization, median filtering, and contrast enhancement to improve image quality and model performance. Experimental results demonstrate improved accuracy, reliable localization, and enhanced interpretability, making the proposed system suitable for clinical decision support.

Keywords — Bone Fracture Detection, Convolutional Neural Network, YOLOv11, Grad-CAM, Fracture Localization, Severity Grading, Explainable AI

I. INTRODUCTION

Bone fractures are among the most prevalent musculoskeletal injuries and require timely and accurate diagnosis to prevent complications such as malunion, infection, and long-term disability. Deep learning-based approaches have been increasingly adopted to improve fracture detection accuracy and clinical decision-making. For instance, Tahir *et al.,* [1] proposed an ensemble deep learning model that combines multiple classifiers to enhance fracture detection performance, demonstrating improved accuracy over single-model approaches. Similarly, Aldhyani *et al.,* [2] utilized deep learning techniques for fracture diagnosis and showed that AI-based systems can significantly improve detection reliability across diverse datasets.

To address computational efficiency, Abdusalomov *et al.,* [3] introduced a lightweight deep learning framework that reduces model complexity while maintaining high accuracy, making it suitable for future medical applications. Pattnaik *et al.,* [4] developed an automated fracture detection system using deep learning, highlighting its effectiveness in assisting clinicians by reducing diagnostic time and human error. In addition, Scutelnicu *et al.,* [5] presented a comprehensive review emphasizing the importance of preprocessing techniques such as normalization and noise reduction in improving fracture detection performance.

Transfer learning has been widely explored to improve model generalization, especially when large annotated datasets are unavailable. Alam *et al.,* [6] demonstrated that transfer learning using pre-trained CNN models significantly enhances fracture detection accuracy and reduces training time. Thota *et al.,* [7] further showed that deep learning-based systems can be effectively deployed in real-time applications, providing fast and reliable fracture detection in clinical environments.

Comparative and advanced learning strategies have also been investigated to improve model performance. Bose *et al.,* [8] conducted a comparative study of different deep learning architectures, concluding that model selection plays a critical role in achieving optimal accuracy. Ruhi *et al.,* [9] proposed an attention-based transfer learning approach that improves fracture classification by focusing on relevant regions in X-ray images, thereby enhancing detection of subtle fracture patterns.

Deep learning techniques have also been applied to specific fracture types and anatomical regions. Chai *et al.,* [10] developed a deep learning model for rib fracture detection, demonstrating the capability of CNN-based approaches to handle complex fracture structures. Qin *et al.,* [11] proposed an AI-assisted diagnostic system that improves fracture detection performance and supports clinical decision-making by

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providing more consistent results. Similarly, Isgor *et al.,* [12] introduced a hybrid deep learning model that combines multiple techniques to improve detection accuracy and robustness.

Review-based studies such as Kutbi *et al.,* [13] highlight the growing role of artificial intelligence in fracture detection and emphasize that preprocessing, model optimization, and feature extraction are critical for improving performance. Meza *et al.,* [14] developed a CNN-based fracture detection system that achieved high classification accuracy, demonstrating the effectiveness of deep learning in identifying fracture patterns. Furthermore, Beyraghi *et al.,* [15] showed that deep neural networks can effectively capture complex structural variations in bone images, improving diagnostic precision.

Despite these advancements, most existing studies primarily focus on fracture detection and do not provide a unified framework for multi-region detection, localization, and severity grading. Additionally, limited attention has been given to explainability, which is crucial for clinical adoption. To address these challenges, the proposed work introduces a comprehensive deep learning framework that integrates multiple CNN architectures (ResNet50, DenseNet121, InceptionV3, and EfficientNetB3) for classification, YOLOv11 for fracture localization, and Grad-CAM for explainable visualization and severity grading. Unlike previous works [1]–[15], which mainly focus on detection accuracy, the proposed system provides an integrated and interpretable solution suitable for real-world clinical applications.

II. LITERATURE SURVEY

Deep learning has significantly advanced automated bone fracture detection and medical image analysis by enabling accurate feature extraction and robust classification from radiographic images. Convolutional Neural Networks (CNNs) and their improved variants have demonstrated strong capability in identifying complex fracture patterns across multiple anatomical regions. Recent research focuses on improving model efficiency, detection accuracy, and real-time applicability, while also incorporating explainability and segmentation techniques for enhanced clinical usability. Advanced architectures such as EfficientNetV2, YOLO-based detection models, and segmentation networks like UNet++ and nnU-Net have further strengthened the performance of deep learning systems in medical imaging applications [16]–[20].

Y. L. Thian *et al.,* proposed a deep learning-based approach for automated fracture detection in radiographic images [16]. Their model demonstrated that CNNs can effectively learn discriminative features from X-ray images and achieve high diagnostic accuracy. The study emphasized the potential of deep learning systems in assisting radiologists by improving detection reliability and reducing diagnostic time. However, the work primarily focused on classification and did not include detailed localization or severity grading.

B. Zhou *et al.,* introduced a method for learning deep discriminative features for localization tasks [17]. This approach laid the foundation for visual interpretability in deep learning by enabling models to highlight important regions in an image. Such techniques are crucial in medical imaging applications, as they improve transparency and allow clinicians to understand and validate model predictions.

X. Zhang *et al.,* presented a comprehensive study on residual networks for medical image classification [18]. Their work demonstrated that residual learning improves gradient flow and enables the training of deeper neural networks, resulting in better feature extraction and classification accuracy. Residual-based architectures have become widely adopted in fracture detection systems due to their ability to handle complex image patterns.

S. Huang *et al.,* proposed a deep learning model using DenseNet for medical image classification [19]. The dense connectivity structure enhances feature reuse and improves information flow across layers, allowing the network to capture fine-grained fracture details. This architecture is particularly effective in identifying subtle fractures that are difficult to detect using conventional methods.

M. Szegedy *et al.,* explored Inception-based architectures for medical image analysis [20]. By utilizing multi-scale convolutional filters, the model captures both local and global features within an image. This capability improves the detection of fractures of varying sizes and shapes, making it suitable for heterogeneous medical datasets.

M. Tan and Q. Le introduced EfficientNetV2, an improved version of EfficientNet that enhances training speed and model efficiency [21]. The architecture uses various scaling terms like depth, width, and resolution, to achieve better accuracy with fewer parameters. This would help future fracture detection systems and helps to perform in various data constrained environments.

C. Bochkovskiy *et al.,* proposed YOLOv4, a real-time object detection model that improves both speed and accuracy [22]. The model enables efficient detection and localization of objects within images, making it highly suitable for identifying fracture regions in X-ray images. Its single-stage detection mechanism allows for faster inference compared to traditional methods.

Z. Zhou et al., proposed UNet++, an improved version of U-Net that uses redesigned skip connections to capture multiscale features more effectively [24]. The architecture reduces the semantic gap between encoder and decoder, leading to better segmentation accuracy and improved boundary detection in medical images. However, the model increases computational complexity compared to standard U-Net.

J. Isensee et al., introduced nnU-Net, a self-configuring framework that automatically adapts network architecture, preprocessing, and training strategies based on the dataset [25].

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The model achieves high segmentation accuracy and strong generalization across various medical imaging tasks, though it requires significant computational resources.

III. PROPOSED METHODOLOGY

The proposed framework presents a hybrid deep learning-based system for automated bone fracture detection, localization, and severity grading from X-ray images. The system integrates Convolutional Neural Networks (CNNs) for classification, YOLOv11 for fracture localization, and Grad-CAM for explainable visualization. Additionally, an Activation Area Ratio (AAR)-based severity grading mechanism is introduced to quantify fracture severity. The architectural workflow is illustrated in Fig. 1, where preprocessing, classification, localization, and interpretability are combined into a unified pipeline. The integration of these components enables end-to-end analysis, reducing dependency on manual diagnosis and improving clinical decision support. Furthermore, the framework is designed to be scalable and adaptable across different anatomical regions, ensuring robustness in real-world medical applications.

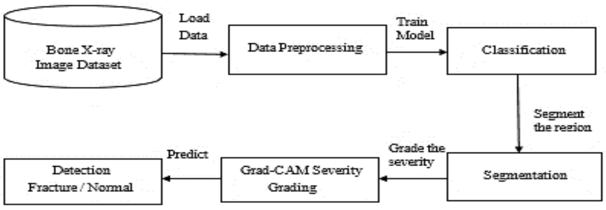

Fig 1: Architectural Workflow of the Proposed Bone Fracture Detection system.

A. Dataset and Preprocessing

The dataset consists of X-ray images collected from multiple anatomical regions such as wrist, hand, femur, and ankle, including both fractured and non-fractured cases. Prior to training, preprocessing is performed to enhance image quality and ensure uniformity, as illustrated in Fig. 2. Each image is resized to a fixed resolution (224×224 for CNN models and 416×416 for YOLOv11). Pixel intensities are normalized to the range [0,1] to ensure stable training. Noise removal is performed using median filtering, which preserves edge details critical for fracture detection while eliminating unwanted artifacts. To improve generalization and reduce overfitting, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied. These augmentations simulate real-world variations in X-ray imaging conditions and enhance model robustness.

Fig 2: Preprocessed Images of the Proposed Bone Fracture Detection system.

B. Fracture Detection using CNN Models

For fracture classification, multiple deep learning architectures including ResNet50, DenseNet121, InceptionV3, and EfficientNetB3 are utilized. These models are pre-trained on ImageNet and fine-tuned on the fracture dataset using transfer learning. The CNN models act as feature extractors, capturing hierarchical representations such as edges, textures, and structural discontinuities in bone regions. The extracted features are passed through fully connected layers followed by a Softmax activation function to classify images into fracture and non-fracture categories. Dropout regularization is applied to reduce overfitting, and the models are trained using the Adam optimizer with an optimal learning rate. The performance of each model is evaluated using metrics such as accuracy, precision, recall, and F1-score, and the best-performing model is selected for further processing.

C. Fracture Localization using YOLOv11

To determine the precise location of fractures, YOLOv11 is employed as a real-time object detection model. As illustrated in Fig. 3, YOLOv11 divides the input image into a grid and predicts bounding boxes along with confidence scores and class probabilities. This approach enables simultaneous detection and localization of fracture regions in a single forward pass, ensuring high efficiency. The output consists of bounding boxes highlighting fracture regions along with confidence scores, providing spatial information necessary for clinical interpretation and treatment planning.

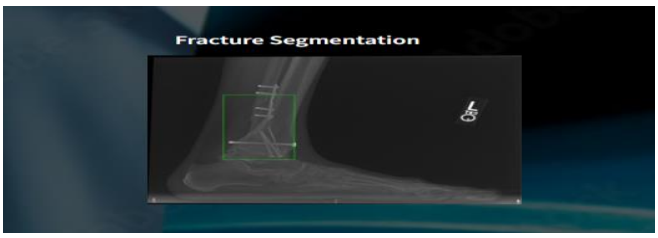

Fig 3: Segmentation of the Fracture Region using Yolov11 Model.

D. Explainability using Grad-CAM

To enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated into the CNN models. Grad-CAM generates heatmaps that highlight the most influential regions contributing to the model's prediction, as shown in Fig. 3. These heatmaps allow clinicians to verify whether the model focuses on relevant fracture regions rather

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than background areas. When combined with YOLOv11 detection, Grad-CAM provides both localization (bounding box) and visual explanation (heatmap), improving transparency and trust in the system.

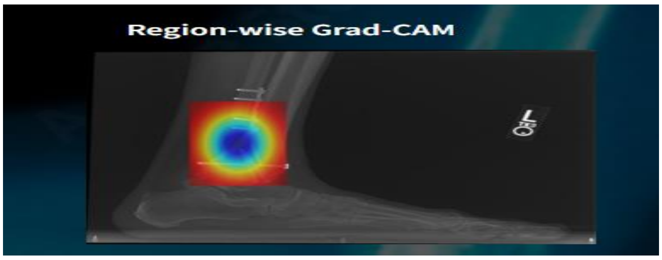

Fig 4: Grad-CAM Heatmap Highlighting the Fracture Detected Region.

E. Severity Grading using AAR

To quantitatively assess fracture severity, an Activation Area Ratio (AAR)-based grading mechanism is proposed, which utilizes Grad-CAM activation maps to measure the extent and intensity of fracture regions. The AAR represents the proportion of activated regions corresponding to fracture areas relative to the total image area, as defined in Eq. (1). This ratio captures the spatial distribution of fracture-related features within the X-ray image.

$$\mathrm{AAR} = \frac{\text{Activated Area}}{\text{Total Area}} \qquad (1)$$

To account for variations in spatial resolution and ensure normalization across different images, a scaling factor γ is applied to obtain a corrected AAR, as expressed in Eq. (2). This correction helps standardize the contribution of the activated region irrespective of image size.

$$\mathrm{AAR}_{\text{corrected}} = \mathrm{AAR} * \gamma \qquad (2)$$

Furthermore, the mean activation intensity is computed from the Grad-CAM heatmap to reflect the strength of feature activation in the detected fracture region. The final severity score is then obtained by combining the corrected AAR with the mean activation value, as defined in Eq. (3). This formulation ensures that both the spatial extent and intensity of the fracture are considered in severity estimation.

$$Severity\ Score = \mathrm{AAR}_{\text{corrected}} * Mean\ Ativation \qquad (3)$$

Based on the computed severity score, fractures are categorized into three clinically relevant classes. A score within the range of 0 to 0.15 is classified as a simple fracture, indicating minimal structural damage. Scores between 0.16 and 0.35 correspond to wedge fractures, which involve moderate fragmentation and displacement. Scores greater than 0.35 are categorized as multifragmentary fractures, representing severe structural disruption with multiple bone fragments. This grading mechanism enables objective and quantitative assessment of fracture severity, providing valuable support for clinical diagnosis and treatment planning.

F. Overall Workflow

The complete workflow of the proposed system is illustrated in Fig. 4. The process begins with preprocessing of input X-ray images, followed by YOLOv11 is then used for precise localization of fracture regions and then CNN-based classification to detect fractures. Grad-CAM is applied to generate heatmaps for interpretability, highlighting regions influencing model predictions. Finally, the AAR-based severity grading mechanism computes the severity score and classifies the fracture into predefined categories. By integrating classification, localization, explainability, and severity grading into a unified framework, the proposed system provides a robust, accurate, and clinically interpretable solution for automated bone fracture detection and analysis.

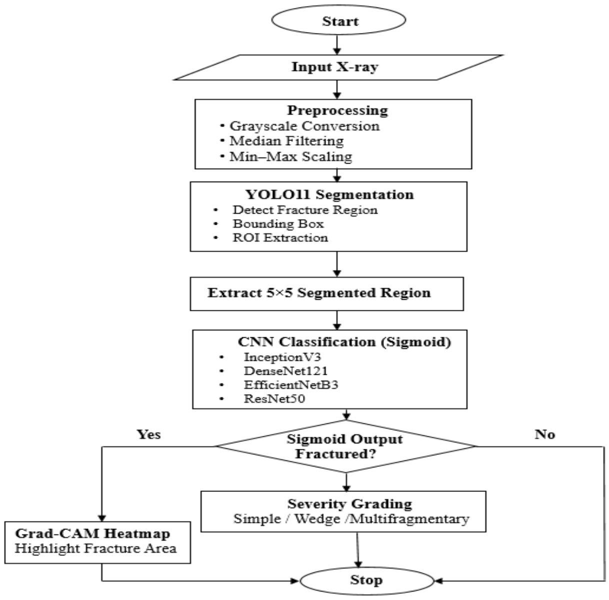

Fig 4: Overall Workflow of the Proposed Bone Fracture Detection system.

IV. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed bone fracture detection system was conducted using a dataset of X-ray images collected from Kaggle, including wrist, hand, femur, and ankle. The dataset consisted of both fractured and non-fractured cases and was divided into training and testing sets in an 80:20 ratio. All images were preprocessed using resizing, normalization, and augmentation methods to improve model generalization. To evaluate model performance, standard metrics including accuracy, precision, recall, and F1-score were used. These metrics provide a comprehensive assessment of the model's ability to correctly identify fracture cases while minimizing misclassification.

A comparative analysis of four CNN architectures InceptionV3, EfficientNetB3, DenseNet121, and ResNet50 was performed to determine the most suitable model for fracture detection. The results, as shown in Fig. 5, indicate that DenseNet121 performance is best showing with a

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precision of 1.00, recall of 0.98, F1-score of 0.99, and accuracy of 0.99. InceptionV3 also demonstrated strong performance with precision of 1.00, recall of 0.97, F1-score of 0.99, and accuracy of 0.99. EfficientNetB3 achieved slightly lower values with precision of 0.97, recall of 0.96, F1-score of 0.96, and accuracy of 0.97. ResNet50 showed comparatively lower performance with precision of 0.94, recall of 0.95, F1-score of 0.95, and accuracy of 0.95. The superior performance of DenseNet121 is attributed to its dense connectivity, which enhances feature reuse and improves gradient flow, enabling better detection of subtle fracture patterns.

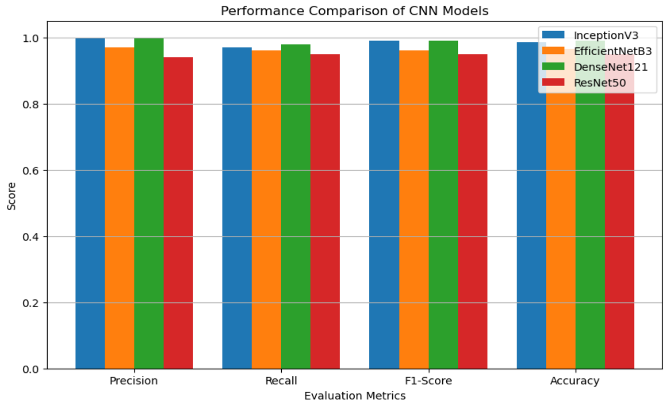

Fig 5: Comparative Analysis of Four CNN Classification Models.

Further analysis was conducted to evaluate the effect of different activation functions using the ResNet50 architecture. The performance of Hard Sigmoid, Tanh, Softmax, and Sigmoid was compared. As illustrated in Fig. 6, the Sigmoid activation function achieved the best performance with precision of 0.95, recall of 0.95, F1-score of 0.95, and accuracy of 0.95. Hard Sigmoid and Tanh showed comparable performance with values around 0.93–0.94, while Softmax exhibited slightly lower performance with values close to 0.92–0.93 across all metrics. The improved performance of the Sigmoid function is due to its smooth gradient behavior and effectiveness in binary classification tasks, ensuring stable convergence.

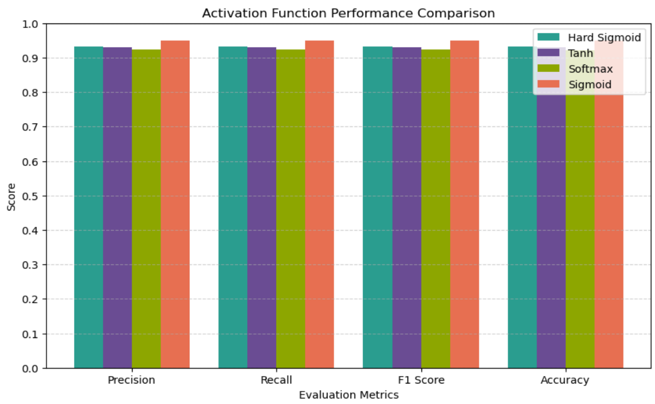

Fig 6: Comparative Analysis of Four Activation Functions.

Based on these results, the Sigmoid activation function was selected for the proposed system has balanced performance and compatibility with explainability methods like Grad-CAM. The final proposed model integrates CNN-based classification, YOLOv11-based fracture localization, and Grad-CAM-based explainability into a unified framework. The model achieved high classification accuracy while YOLOv11 effectively localized fracture regions using bounding boxes. Grad-CAM visualization further enhanced interpretability by highlighting the regions influencing model predictions, enabling clinicians to validate the results. Additionally, the AAR-based severity grading mechanism successfully quantified fracture severity by combining spatial activation and intensity information. Based on the computed severity score, fractures were classified into simple, wedge, and multifragmentary categories, providing clinically meaningful insights for diagnosis and treatment planning.

Table I: Comparative Analysis of Existing Methods and Proposed Work.

Ref	Method	Contribution	Limitation	Advantage
[1]	Ensemble CNN	Improves accuracy	No localization, no XAI	Adds YOLO + Grad-CAM + grading
[3]	Lightweight CNN	Fast computation	Low feature learning, no grading	Better CNN + severity grading
[6]	Transfer Learning	Better generalization	No localization/XAI	Adds detection + explainability
[9]	Attention Model	Focused feature learning	High complexity, no grading	Simpler + integrated grading
[10]	CNN (Rib)	Specific fracture detection	Limited generalization	Multi-region detection
—	**Proposed**	**CNN + YOLO + Grad-CAM + AAR**	—	**Full system: detection + XAI + grading**

The comparative analysis presented in Table I highlights the strengths and limitations of existing bone fracture detection methods in relation to the proposed system. Ensemble-based approaches [1] improve classification accuracy but lack localization and interpretability. Lightweight CNN models [3] offer faster computation but compromise feature learning and do not provide severity analysis. Transfer learning methods [6] enhance generalization; however, they do not incorporate localization or explainability. Attention-based models [9] improve feature

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focus but increase computational complexity and still lack severity grading. Similarly, models designed for specific fracture types [10] show limited generalization across multiple anatomical regions. In contrast, the proposed work integrates CNN-based classification, YOLOv11-based localization, Grad-CAM-based explainability, and AAR-based severity grading into a unified framework. This comprehensive approach not only improves detection performance but also provides interpretable and clinically meaningful outputs, making it more effective for real-world medical applications.

V. CONCLUSION

In this study, a comprehensive deep learning-based framework for automated bone fracture detection, localization, and severity grading was proposed. The system integrates multiple Convolutional Neural Network (CNN) architectures for fracture classification, YOLOv11 for precise localization of fracture regions, and Grad-CAM for explainable visualization. Additionally, an Activation Area Ratio (AAR)-based severity grading mechanism was introduced to quantitatively assess fracture severity and classify it into clinically relevant categories.

Experimental results demonstrated that advanced CNN models such as DenseNet121 and InceptionV3 achieved high classification performance, while ResNet50 with Sigmoid activation provided a balanced and efficient solution for the proposed framework. The integration of YOLOv11 enabled accurate localization of fracture regions, and Grad-CAM visualizations improved interpretability by highlighting the regions influencing model predictions. Furthermore, the AAR-based approach effectively quantified fracture severity, enabling classification into simple, wedge, and multifragmentary fractures.

Compared to existing methods, the proposed system offers a unified solution that combines classification, localization, explainability, and severity grading within a single framework. This integrated approach enhances diagnostic accuracy, reduces reliance on manual interpretation, and provides clinically meaningful insights for decision-making.The proposed system has significant potential for real-world clinical applications, including computer-aided diagnosis, emergency care, and telemedicine. Future work will focus on expanding the dataset with multi-modal imaging, incorporating advanced attention-based architectures, and optimizing the model for deployment in real-time and edge-based medical systems.

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