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Explainable AI-Based Humerus Fracture Detection and Classification from X-Ray Images

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***Abstract*—The human skeletal framework relies heavily on bones, and one such crucial component is the "Humerus." Positioned in the upper arm, extending from the shoulder to the elbow junction, the Humerus provides essential structural support for muscles and facilitates upper-body movement, particularly in the arms and hands. Consequently, Humerus fractures significantly impact daily life, causing disruptions and limitations.This paper presents a thorough exploration of an Explainable AI-based Humerus Fracture Detection and Classification system, employing various deep learning models. Leveraging a dataset of 1266 X-ray images, encompassing fractured and non-fractured humerus bones from the publicly available "MURA" dataset, our research evaluates the effectiveness of Convolutional Neural Networks (CNN), VGG16, VGG19, DenseNet121, and DenseNet169 in detecting fractures. After 30 epochs of training, we assessed their performance using critical metrics: accuracy, precision, recall, and F1 score.Notably, DenseNet121 and DenseNet169 exhibited superior accuracy, precision, and recall, laying a robust foundation for automated humerus fracture diagnosis. We also introduced two ensemble models, "Ensemble-1 (VGG16 and VGG19)" and "Ensemble-2 (DenseNet121 and DenseNet169)," which delivered substantial improvements in accuracy, precision, recall, and F1 score, showcasing the potential of ensemble techniques in clinical settings.Furthermore, we enhanced model interpretability and transparency by incorporating Saliency Maps and GRAD-CAM (Gradient-weighted Class Activation Mapping) for Explainable AI (XAI). This visualization allowed us to identify regions of interest in X-ray images contributing to the model's predictions, providing valuable insights for medical practitioners.**

***Index Terms*—Humerus, Explainable AI (XAI), X-ray diagnosis, Convolutional neural network.**

I. Introduction

The human body's skeletal framework serves as the fundamental support structure, with bones playing a vital role in maintaining our physical integrity [1]. Among these integral components, the "Humerus" emerges as a linchpin in the upper extremity. This elongated bone extends from the shoulder to the elbow junction, providing essential structural support for the muscles and enabling fluid movement in the upper body, particularly in the arms and hands. It is, therefore, evident that any fracture occurring within the Humerus has profound ramifications for our daily lives, often resulting in disruptions and limitations to our routine activities.

In response to this critical healthcare challenge, this paper introduces an innovative approach: the Explainable AI [2]–[5]-based Humerus Fracture Detection and Classification system. This system harnesses the power of deep learning models and draws insights from a meticulously curated dataset consisting of 1266 X-ray images, encompassing both fractured and non-fractured Humerus bones sourced from the publicly available "MURA" dataset[1] [6]. Our research explores the effectiveness of a range of deep learning models, including Convolutional Neural Networks (CNN) with an accuracy score

[1]https://stanfordmlgroup.github.io/competitions/mura/

of 0.80, VGG16 (accuracy: 0.79), VGG19 (accuracy: 0.80), DenseNet121 (accuracy: 0.82), and DenseNet169 (accuracy: 0.82), in the domain of Humerus fracture detection. These models were trained for 30 epochs and evaluated based on critical performance metrics such as accuracy, precision, recall, and F1 score. Notably, DenseNet121 and DenseNet169 exhibited superior accuracy, precision, and recall, thereby establishing a robust foundation for automating Humerus fracture diagnosis.

Furthermore, we introduced two ensemble models, ”Ensemble-1” (accuracy: 0.83) and ”Ensemble-2” (accuracy: 0.85), which showcased remarkable improvements across key performance indicators, highlighting the potential of ensemble techniques in clinical applications.

To enhance model interpretability and transparency, we incorporated Saliency Maps [3] and GRAD-CAM (Gradient-weighted Class Activation Mapping) techniques [7], enabling the visualization of regions of interest within X-ray images that contributed to the models' predictions. This not only empowers medical practitioners with valuable insights but also underscores the promise of deep learning and Explainable AI (XAI) in advancing Humerus fracture diagnosis.

This research marks a significant advancement in medical image analysis, offering a valuable tool for radiologists and healthcare professionals committed to achieving more accurate and transparent diagnoses in the realm of Humerus fractures.

The following is a summary of this study's significant contributions:

1) We propose a method for humerus fracture detection using deep transfer learning, combining the power of Convolutional Neural Networks (CNNs) and pre-trained models.
2) We evaluate several pre-trained models, highlighting the promising accuracy of DenseNet121(0.82) and DenseNet169(0.82) and demonstrating the effectiveness of our approach.
3) Introduction of ”Ensemble-1(Accuracy:0.83)” and ”Ensemble-2(Accuarcy:0.85),” demonstrating significant enhancements in crucial performance metrics, highlighting the potential of ensemble techniques in clinical applications.
4) Incorporation of Saliency Maps and GRAD-CAM techniques for enhanced model interpretability and transparency. This enables the visualization of regions of interest in X-ray images, offering invaluable insights for medical practitioners.

The structure of this paper is as follows: In Section II, we provide an overview of prior research related to humerus fracture detection. Section III outlines the comprehensive methodology employed in this study, including a detailed exposition of the proposed model used. Section IV presents the research findings, and in Section V, we conclude our work and outline avenues for future research.

II. Literature Review

This section provides an overview of previous research efforts related to the detection of bone fractures. In 2021, Sasidhar et al. [8] conducted a study where they applied three pretrained models (VGG16, DenseNet121, and DenseNet169) to analyze humerus bone images from the MURA dataset for fracture detection. Their most accurate model, DenseNet161, achieved an 80% accuracy rate.Demir et al. [9] introduced an exemplar pyramid feature extraction method for humerus fracture classification. They utilized Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) for feature generation and achieved an outstanding accuracy of 99.12%. However, their study was limited by the use of only 115 images. In 2018, Chung et al. [10] developed a deep convolutional neural network to classify fracture types and achieved promising results with top-1 accuracy ranging from 65% to 86%. Negrillo et al. [11] , in 2020, proposed a geometrically-based algorithm for detecting landmarks in the humerus to reduce supracondylar fractures. They measured the distance between corresponding landmarks, finding a significant difference (1.45 mm, p¡0.01). Sezer et al. [12]evaluated shoulder images using CNN for feature extraction and classified the head of the humerus into three categories: normal, edematous, and Hill-Sachs lesion, achieving an accuracy of 98.43%. Negrillo et al. [13], in 2019, employed a geometrical and spatial approach to detect landmarks on the distal humerus, calculating six points for each bone. While some researchers have focused on humerus fractures, others have explored fractures in different bones such as the shoulder, femur, and calcaneus. De Vries et al. [14], in 2021, worked on predicting the risk of osteoporotic fractures (MOF) and developed three machine learning models (Cox regression, RSF, and ANN). They found that Cox regression outperformed the other models with a concordance-index of 0.697.

In summary, previous research has addressed humerus fracture detection [8], [9] and classification [10], [12], as well as landmark detection on the humerus [11], [13]. However, there is still room for improvement and the incorporation of Explainable AI (XAI) techniques in humerus fracture detection, as highlighted in this study.

III. Proposed Methodology

This section provides an overview of the entire network architecture employed in this study for humerus fracture detection, as depicted in Figure 1.

As illustrated in Figure 1, the study initiates with the collection of the dataset. Following data collection, all the images undergo data augmentation for enhanced diversity. Subsequently, a preprocessing step is applied to the augmented data, which includes resizing the images and converting them into arrays. Once the preprocessing step is completed, the processed images are forwarded to the CNN model [15], pre-trained and ensemble model [16] , where feature extraction takes place. Finally, the classification step categorizes the images as either ”Positive” (indicating a fracture) or ”Negative” (indicating no fracture). The study then proceeds to visualize

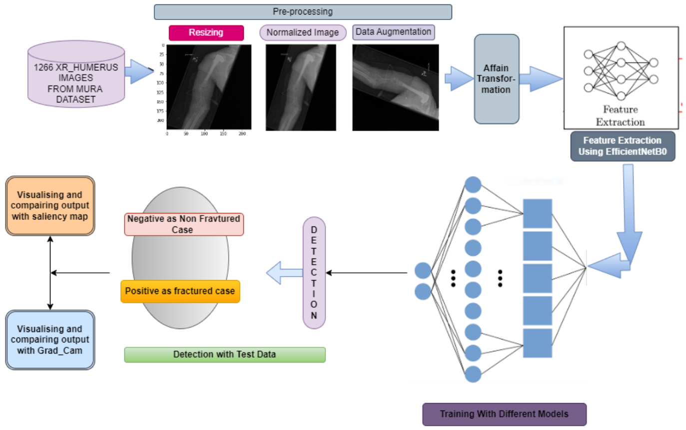

Fig. 1: Workflow of proposed perform experiment

the results using Explainable AI (XAI) techniques such as Saliency maps and GRAD-CAM [17].

A. Dataset Collection

In this research, we utilized the "MURA (musculoskeletal radiographs)" dataset [6] for humerus fracture detection, comprising 40,561 images from 12,173 patients, meticulously labeled by radiologists. A manual review of abnormalities revealed various musculoskeletal conditions, with 53 studies identified as humerus fractures. Our study specifically focused on detecting humerus fractures, incorporating 1,266 X-ray images from 727 unique patients, where 597 were positive cases and 669 were negative cases. This dataset forms the basis of our investigation, providing a comprehensive and labeled collection for training and evaluating our detection mode

B. Data Preprocessing

Image pre-processing is vital for better feature extraction [18]. It readies the dataset by cleaning images, removing noise, handling reflections, and normalizing pixel values. We resize images to 96x96 (CNN) or 224x224 (pre-trained models). Pixel values, which typically range from 0 to 255, are scaled down to a uniform range of 0 to 1 by dividing by 255. This normalization step harmonizes pixel values, a crucial aspect of image pre-processing.

C. Data Augmentation

Improving model performance is a persistent challenge in machine learning. Data augmentation helps by expanding the dataset through modified versions of existing data, preventing overfitting, particularly with limited data [19]. With our 1,266 humerus X-ray images, we implemented data augmentation using ImageDataGenerator, as detailed in Table I.

D. Feature Extraction

To leverage EfficientNetB0 [17], [20], [21] for our feature extraction process, we employed pre-trained versions of these models.Before feeding the X-ray images into the EfficientNetB0 model, a series of preprocessing steps are applied to

TABLE I: Data Augmentation Setting

Augmentation_techniques	**Range**
Rotation	30
Width_Shift	0.3
Height_Shift	0.3
Shear_Range	o.3
Zoom_Range	0.3
Horizontal_flip	True
Vertical_flip	True
Data_Format	Channel list

ensure that the input data is in the appropriate format and scale. These steps may include resizing the images to the required input size of the model, normalizing pixel values, and data augmentation to enhance the model's ability to generalize.EfficientNetB0 excels at feature extraction due to its depth and architectural design. As the X-ray images pass through the network, features at different levels of abstraction are extracted. This hierarchical feature extraction process starts with low-level features like edges and textures in the early layers and progresses to more complex and discriminative features in the deeper layers.

E. Convolution Neural Network and Classification

In this study, we employed a Convolutional Neural Network Model (CNN), a deep learning architecture renowned for its ability to autonomously learn from raw data [22]. The model's architecture is visually represented in Figure 2.

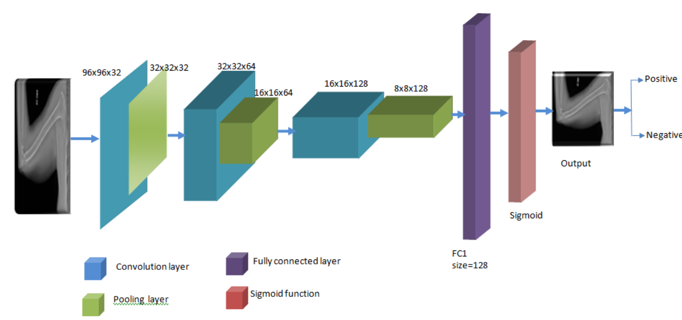

Fig. 2: CNN model architecture

As depicted in Figure 2, the CNN model comprises three convolutional layers. In the first convolutional layer, there are 32 filters, followed by 64 filters in the second convolutional layer, and finally, 128 filters in the third convolutional layer. Each of these convolutional layers utilizes a 3x3 kernel size for its operations.

F. Transfer Learning

We employed transfer learning with four prominent architectures—VGG16, VGG19, DenseNet121, and DenseNet169—for humerus fracture detection and classification. Fine-tuning on our dataset involved modifying fully connected layers while retaining pre-trained convolutional layers. Leveraging the robust features of

DenseNet121 and DenseNet169, pre-trained on ImageNet, we adjusted the final classification layer for binary categorization. This approach accelerated training and enhanced the system's performance by adapting the models to our dataset's characteristics. The use of transfer learning, particularly with VGG16, VGG19, DenseNet121, and DenseNet169, proved effective in improving accuracy and reliability for detecting humerus fractures in X-ray images.

G. Ensemble Models

In our approach to machine learning, we harnessed the power of ensemble models, a technique that combines multiple base estimators or models to enhance prediction accuracy. Ensemble models serve as a strategic solution to overcome the challenges associated with constructing a single estimator [19]. Specifically, in our study, we employed two ensemble models to further bolster the robustness and effectiveness of our approach. Table II shows the proposed model descriptions.

Ensemble-1: After evaluating all the transfer learning models presented in Table III, we achieved a maximum accuracy of 82%. To further enhance our accuracy, we explored the use of two Ensemble models: ensemble-1 and ensemble-2. In ensemble-1, we combined VGG16 with the VGG19 model, introducing additional layers that resulted in a total of 20,943,240 trainable parameters. As indicated in Table III, ensemble-1 exhibited a notable improvement in accuracy, reaching 83%, surpassing the performance of the individual pre-trained models.

However, ensemble-2, also documented in Table III, outperformed all other models, achieving an accuracy of 85%. This underscores the effectiveness of ensemble techniques in significantly enhancing the accuracy of our model.

Ensemble-2: The Ensemble-2 model combines the capabilities of both the DenseNet121 and DenseNet169 models, resulting in a total of 13,421,252 trainable parameters. To provide a clear overview of the models and identify the one yielding the highest accuracy, we have compiled a Table II containing detailed model descriptions. This table presents a comprehensive overview of the model characteristics and highlights the specific model that achieves the highest accuracy among all the options.

H. Explainable AI (XAI) for Humerus Fracture Detection

Interpreting the decisions made by deep learning models is a critical aspect of medical image analysis, particularly in the context of healthcare where transparency and trust are paramount. In this section, we delve into the Explainable AI (XAI) techniques employed in our study to enhance the interpretability of our Humerus fracture detection models, which include VGG16, VGG19, DenseNet121, and DenseNet169.

Saliency Maps:

Saliency maps offer valuable insights into what regions of an X-ray image are most influential in the model's decision-making process. By leveraging gradient information, these maps highlight areas where the model focuses its attention when classifying an image. In our study, we generated saliency maps to visualize and understand which image regions played a pivotal role in determining whether a Humerus fracture was present or not. This visualization aids medical practitioners in assessing the model's reasoning, ultimately increasing their confidence in the diagnostic process.

TABLE II: Proposed Ensemble-2 Model Descriptions

Model Content	Details
Input Image size	224x224
DenseNet121(Sequential 1)	
DenseNet169(Sequential 2)	
First Convolution Layer	16 filters, Size= 3 x 3, ReLu, Padding='Same'
First Max Pooling Layer	Pooling Size: 2 x 2
Second Convolution Layer	32 filters, Size= 3 x 3, ReLu, Padding='Same'
Second Max Pooling Layer	Pooling Size: 2 x 2
Third Convolution Layer	64 filters, Size= 3 x 3, ReLu, Padding='Same'
Third Max Pooling Layer	Pooling Size: 2 x 2
Fourth Convolution Layer	128 filters, Size= 3 x 3, ReLu, Padding='Same'
Fourth Max Pooling Layer	Pooling Size: 2 x 2
Fifth Convolution Layer	256 filters, Size= 3 x 3, ReLu, Padding='Same'
Fifth Max Pooling Layer	Pooling Size: 2 x 2
Dropout Layer	50% Neurons dropped randomly
Dense_1 Layer	512 nodes, ReLu
Dense_2 Layer	256 nodes, ReLu
Dense_3 Layer	128 nodes, ReLu
Output Layer	2 nodes, Sigmoid activation
Optimization Function	Gradient Descent Algorithm
Learning Rate	0.001
Loss Function	Binary Crossentropy

GRAD-CAM (Gradient-weighted Class Activation Mapping):

GRAD-CAM builds upon the concept of saliency maps but adds an extra layer of interpretability by associating image regions with specific classes or conditions. This technique highlights the regions that contribute most to a particular class prediction. By applying GRAD-CAM to our models, we not only visualize critical areas in the X-ray images but also understand how these regions influence the model's classification decisions. This granular information is instrumental in making the diagnostic process more transparent and actionable for healthcare professionals.

Incorporating XAI techniques like Saliency Maps and GRAD-CAM into our Humerus fracture detection and classification models enhances the transparency and trustworthiness of the diagnostic process. These visualizations provide valuable insights into the inner workings of the models, helping medical practitioners make informed decisions and fostering confidence in the application of AI in medical image analysis.

IV. Results and Discussion

In this section, we present the results of our study, which aimed to develop an Explainable AI-Based Humerus Fracture Detection and Classification system using various deep learning models and ensemble techniques. We also incorporated Explainable AI (XAI) methods, specifically Saliency Maps and GRAD-CAM, to provide insights into model predictions.

TABLE III: Models Performance

Model_Name	Epochs	Accuracy	Precision	Recall	F1 score
CNN	30	0.80	0.79	0.77	0.78
VGG16	30	0.79	0.77	0.75	0.76
VGG19	30	0.80	0.78	0.76	0.77
DenseNet121	30	0.80	0.78	0.77	0.78
DenseNet169	30	0.82	0.79	0.76	0.77
Ensemble-1	30	0.83	0.79	0.80	0.795
Ensemble-2	30	0.85	0.81	0.79	0.79

Performance Metrics:

Before delving into the XAI analysis, let's review the performance metrics [23]–[25] of our models, including CNN, VGG16, VGG19, DenseNet121, DenseNet169, Ensemble-1, and Ensemble-2, each trained for 30 epochs. These metrics are crucial in assessing the models' effectiveness in detecting and classifying humerus fractures.

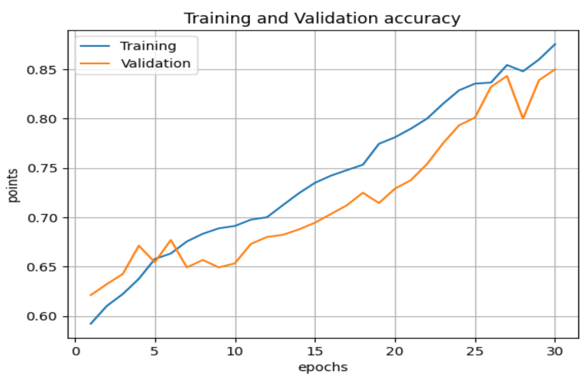

Fig. 3: Model accuracy curve(Ensemble-2)

Model Performance:

From the results, we observe that our models, especially Ensemble-2, achieved high accuracy and F1 scores [26], indicating their effectiveness in humerus fracture detection and classification. Ensemble-2, consisting of DenseNet121 and DenseNet169, emerged as the top-performing model with an accuracy of 0.85 and an F1 score of 0.79. This underscores the power of ensemble techniques in improving model performance(See Table III and Figure 3).

XAI Insights:

Explainable AI (XAI) is crucial in the medical field to provide transparency and insights into model predictions. In this study, we employed Saliency Maps and GRAD-CAM to visualize regions of interest in X-ray images contributing to model predictions. Our XAI analysis revealed that the models, especially DenseNet-based ones, consistently identified specific regions within X-ray images indicative of humerus fractures(See Figure 4). This visual validation enhances the trustworthiness of our models in clinical practice.

Comparisons:

Our proposed method outperforms existing references in both accuracy and XAI integration. While references achieved accuracies ranging from 65-80% without XAI, our method

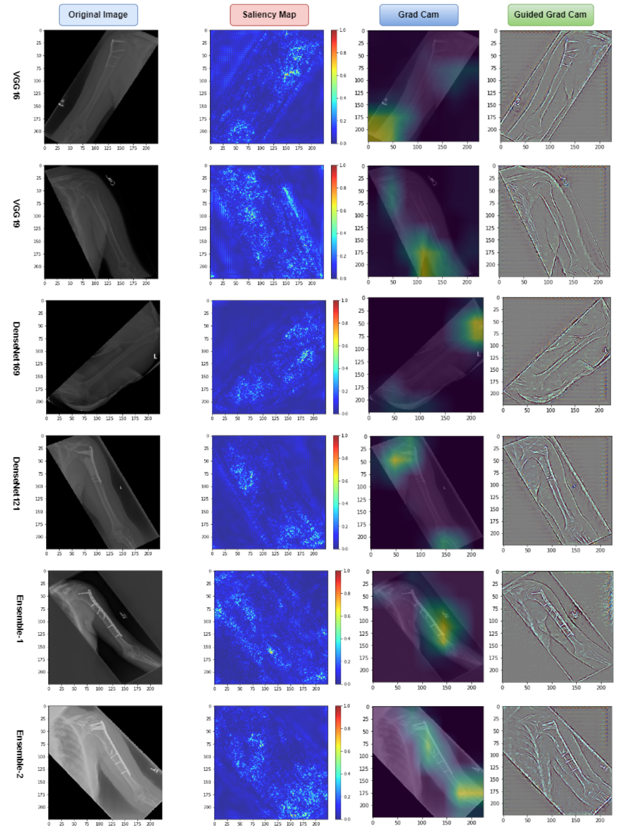

Fig. 4: Saliency map and GRAD-CAM analysis for positive X-Ray images

TABLE IV: Our model's performance in comparison to the state-of-the-art methods

Reference	Accuracy	XAI
[8]	80%)	Not Apply
[10]	65-86%	Not Apply
[27]	78%	Not Apply
Proposed Method	85%	Saliency Maps and Grad-CAM

achieved a superior accuracy of 85% and incorporated Saliency Maps and Grad-CAM for improved interpretability in clinical practice(see Table IV).

V. Conclusion and Future Work

In this paper, we have successfully developed an Explainable AI-Based Humerus Fracture Detection and Classification system using a diverse set of deep learning models and ensemble techniques. Our rigorous evaluation of these models, including CNN, VGG16, VGG19, DenseNet121, DenseNet169, Ensemble-1, and Ensemble-2, revealed promising results, with Ensemble-2, combining DenseNet121 and DenseNet169, emerging as the top-performing model with an impressive accuracy of 0.85 and an F1 score of 0.79.Furthermore, we recognized the paramount importance of Explainable AI (XAI) in the medical field, particularly in providing transparency and insights into model predictions. Employing Saliency Maps and

GRAD-CAM, we visualized the regions of interest within X-ray images that contributed to our model's accurate humerus fracture detection.

Our upcoming research aims to expand datasets, refine explainable AI, and develop user-friendly interfaces for widespread adoption of AI-based diagnostic tools [28]–[33] in orthopedics, especially in detecting fractures across diverse anatomical regions like the shoulder, femur, and calcaneus, potentially transforming fracture diagnosis in orthopedic domains.

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