

YEG-Net: A Compact Deep Learning Model for Accurate Bone Fracture Analysis

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ABSTRACT

Bone fracture detection in medical imaging is crucial for emergency care. This is especially true in children. Quick and precise diagnosis can significantly influence treatment results. Manually interpreting X-ray images often involves human error, differences among observers, and a lack of expert radiologists, particularly in areas with limited resources. To address all these issues, we have studied and proposed a hybrid deep learning model YEG-Net which was fully known as combines three effective components. First, 'Y' as YOLOv8 for real-time and accurate fracture localization. Second, 'E' as EfficientNet-B0 for lightweight and precise fracture detection. type classification, and lastly 'G' as Grad-CAM full suite i.e including Grad-CAM, Grad-CAM++, Score-CAM for providing clear visual explanations that are relate to bone fracture. The system uses the FracAtlas dataset for training and evaluation and this dataset includes labelled X-ray images of fractures in all types. The YOLOv8 model which detects the fracture areas and will make bounding boxes around the fracture areas in X-rays The system crops the boxes and sends them to an EfficientNet-B0 classifier for classification. After classification, here the app Grad-CAM suite was applied to highlight the regions related to fracture areas, which improves clinical understanding. Our hybrid model reaches a mean Average Precision (mAP) of 87.4% for detection and a classification accuracy of 90.2%. It outperforms standalone models. The suggested hybrid model brings together localization, classification, and explainability into a full pipeline. This hybrid model can be used in real-time diagnostic analysis. The final hybrid model that was proposed will bring all together localization, classification, and explainability into a full framework.

1. INTRODUCTION

Background:

Bone fractures are among the most common medical emergencies, especially in children and athletes[1]. Injuries to the wrist, hand, and arm are common. They need a fast and accurate diagnosis to guarantee effective treatment. Studies show that nearly one-third of children in the UK experience at least one fracture before age 17. X-rays are the most common way to diagnose fractures because they are cheap and easy to get. These specialists can be difficult to find in rural or low-resource areas[2]. Manual interpretation can also differ between observers and is prone to human error [3]. To address these problems, recent advances in artificial intelligence, especially deep learning, have shown promise in automating medical image analysis. This can make clinical decision making faster and more reliable.

Existing Evidence:

In medical images, Many deep learning models have been created to identify and categorize objects[4]. YOLO (You Only Look Once), especially its latest version, YOLOv8, has shown strong performance in real-time object localization tasks. This includes identifying fracture regions in X-rays. EfficientNet-B0 is a lightweight and scalable convolutional neural network. It have obtained the great results in classifying and identifying medical images[5][6]. Explainable AI (XAI) tools like Grad-CAM, Grad-CAM++, and Score-CAM have created heatmaps to illustrate where the model focuses during decision-making. This enhances transparency and builds trust among clinicians. Previous studies have used some of these technologies, but they often lacked complete integration or specific datasets.

Research Gap:

Although several models have addressed either detection or classification, few provide a unified framework that combines detection, classification, and visual explainability. Moreover, current systems seldom focus on upper-limb fractures or use a publicly annotated dataset like FracAtlas[7]. To our knowledge, no previous study has combined YOLOv8, EfficientNet-B0, and the complete Grad-CAM suite on the FracAtlas dataset. This approach aims to provide a complete, real-time, clear solution for bone fracture analysis[8].

Objective:

This research introduces a new hybrid deep learning framework that combines YOLOv8 for real-time fracture detection, EfficientNet-B0 for classifying fracture types (comminuted, simple, and hairline), and the Grad-CAM suite for visual explanations. The goal is to create a clear, efficient model to help radiologists diagnose upper-limb fractures using X-ray images[9].

Scope and Constraints:

The novelty looks at finding and identifying wrist and hand fractures in 2D radiographs using the FracAtlas dataset[10]. It looks at three fracture categories and relies solely on publicly available data. Limitations include poor generalization to other body parts or imaging methods, such as CT and MRI, as well as dependence on a single dataset, which may not cover all clinical variations. However, the proposed model provides a good balance between performance and clarity, making it suitable for use in real-world medical situations.

Contribution #1: This paper demonstrates how deep learning can be applied in orthopaedics using a single model to identify fractures, classify them, and offer visual explanations based on upper-limb X-rays. This supports diagnosis, surgical planning, and triage automation.

Contribution #2: This model addresses the challenge of limited data by using the public FracAtlas dataset. It improves understanding by using Grad-CAM variations that produce clear outputs for clinical validation.

Contribution #3: The model includes YOLOv8, EfficientNet-B0, and Grad-CAM. These tools match today's deep learning techniques in orthopaedics. They include AI-assisted diagnosis, better surgical guidance, and smart imaging platforms.

Contribution #4: This novelty checks the model's reliability through careful evaluation with different metrics and visual checks. It meets key standards such as dataset quality, model validation, and transparency.

Contribution #5: Although it uses 2D radiographs, the model's design allows future integration of various data types with fusion techniques. This will provide deeper diagnostic insights across multiple imaging methods.

2. LITERATURE REVIEW

Bone fracture detection using deep learning is a growing area with more importance in healthcare. Quickly identifying fractures is especially important in busy emergency rooms or in rural areas with few radiologists. Manually interpreting X-rays might result in prejudice and mistakes[11]. Advances in AI, particularly deep learning models like YOLO and EfficientNet, show a lot of potential in automating fracture detection and improving diagnostic accuracy. Many have used deep learning models for object recognition and classification in medical images[12]. Most current systems lack explainability, which is essential for clinical use. Additionally, previous research relies on proprietary or small datasets, which makes it hard to replicate and scale[12].

The 'white et al' as proposed a hybrid model that uses one of the object detection model which is YOLOv5 for localization and EfficientNet-B3 for classification which has been reached high accuracy in telling apart intra- and extra-articular distal radius fractures and This could reduce the need for unnecessary CT

scans[13]. Yaseen et al was written a paper the approach used is two-stage that has been used YOLOv8 for detection and a then the CNN with Grad-CAM for classification showed effective results in detecting the spine fractures from CT images[14]. Yaseen was developed a model here used YOLOX for object detection and GhostNetv2 for classification, which improved diagnostic accuracy for nasal bone fractures from CT images[15]. Tseng multistage CNN with Grad-CAM classified proximal femur fractures and helped junior doctors improve their diagnostic accuracy[16]. It surpassed standard CNNs and EfficientNet variants. Here the model which is hybrid that used EfficientNet-B3 for feature extraction purpose and SVM for classification purpose reached 93.5% accuracy in detecting hand fractures areas[17]. On the GRAZPEDWRI-DX dataset, the YOLOv9 and YOLOv8-clas models surpassed earlier benchmarks in classifying wrist fractures, using EigenCAM for explanation. The end-to-end CNN framework has showed a better significant improvements in processing both time and prediction accuracy through dynamic ROI selection. A bifunctional model that combined YOLOX and Swin-Transformer surpassed EfficientNet in classifying developmental stages with hand bone images. Two ensemble models worked well in classifying humerus fractures, supported by Grad-CAM heatmaps for clearer insights. A new attention-driven transfer learning model achieved over 90% accuracy in classifying fractures from musculoskeletal radiographs. Here the one of the CAD system has been used YOLOv5 for the detection of vertebra area fractures and then InceptionV3 for the classifying purpose of spinal bone metastasis and by using Grad-CAM improved the clinical interpretability and visualization[18]. The models which are CoAtNet and EfficientNetV2 classified bone marrow areas fracture with high precision results, while the Grad-CAM which was helped in mainly for visualize important areas of features[19]. This model used deep

learning and texture analysis for wrist fracture detection, achieving 98% accuracy. The model has achieved precise classification and visualization of calcaneal fractures from X-ray images using Grad-CAM visuals through heatmaps. It identified intertrochanteric fractures with a 97% mean average precision using YOLOv5[20]. Grad-CAM was offered the interpretability and also the outperformed Faster R-CNN was used. With the fracture area of plain wrist radiographs, the CNN results reached 90% accuracy in telling the apart normal, fractured, and occult cases, supported by the Grad-CAM that has used. Grad-CAM visualizations matched clinical bone regions, which improved osteoporosis classification using standard knee radiographs[21].

3. MATERIALS AND METHODOLOGY

This study introduces a mixed deep learning method for detecting, classifying, and visualizing bone fractures. Here the dataset which is FracAtlas has upper-limb X-ray images and these are used in model[22]. The system consists of three main parts: locating fractures with YOLOv8, classifying fracture types with EfficientNet-B0, and providing visual interpretability with Grad-CAM, Grad-CAM++, and Score-CAM. In Figure-1 is the diagram that outlines the full hybrid pipeline that was used in the study. It starts with yolov8 for the purpose of localizing the fracture regions in x-ray images. Then, cropped regions will go through efficientNet-B0 for the classification, and then followed by Grad-CAM for visualization purpose

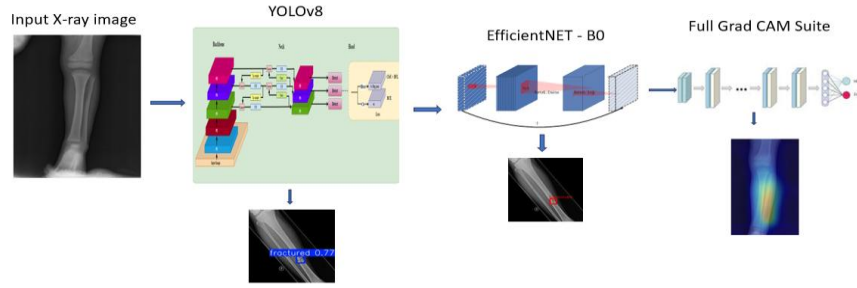


figure 1: WORK FLOW DIAGRAM

I. Data collection:

The dataset used, It is a publicly available collection of annotated radiographic images, mainly for upper-limb bone fracture analysis "[23]. It contains over 4,000 high-resolution X-ray images of the hand and wrist, including both fractured and non-fractured cases.

Each image in this dataset has expert-verified YOLO format annotations. These include bounding boxes that show that identifies the type of fracture. The structured annotation format in this dataset supports both object detection, which locates the fracture, and multi-class classification, which predicts the fracture type. This aligns with the goals of the proposed model. To ensure generalization and robust performance evaluation, the dataset was randomly split into training (70%), validation (15%), and testing (15%) subset

II. Data Preprocessing

Normalization was applied using standard ImageNet mean and standard deviation values for the classifier and pixel scaling to [0, 1] for the detector. To improve the model robustness and prevent overfitting, we have used the several data augmentation techniques during training, which are random flips, rotations, scaling, brightness adjustments, and mosaic augmentation. The model building steps are allowed the models to adapt to variations commonly seen in clinical imaging[24]

III. YOLOv8 Architecture for Localizing Bone Fractures:

The YOLOv8 model will be the first step to build the hybrid model and for that we need to train the YOLOv8 model to identify and localize bone fracture regions in X-ray images from the FracAtlas dataset[25]. We have used the Ultralytics YOLOv8 framework and applied image preprocessing, including resizing and normalization. We trained the model with annotated images that had bounding boxes for comminuted, simple, and hairline fractures. By using anchor-free detection and CIoU loss the model as been improved.

After completing the training and building the model, YOLOv8 model was accurately identified fracture areas and produced bounding boxes with class labels and confidence scores[26]. The outputs from the YOLOv8 module were used to perform further classification in the hybrid system.

YOLOv8 Loss Function

$$LYOLO = \lambda_{cls} \cdot L_{cls} + \lambda_{box} \cdot L_{IoU} + \lambda_{obj} \cdot L_{obj}$$

Complete IoU (CIoU) loss

$$LCIoU = 1 - IoU + c2\rho2(b, b_{gt}) + \alpha v$$

VIII. Evaluation

The hybrid model is evaluated with performance metrics. For YOLOv8, we used precision, recall, and IoU to assess the accuracy of fracture localization. For the EfficientNet-B0 we measured accuracy and F1-score and also used a confusion matrix to analyze predictions for comminuted, simple, and hairline fractures. "The effectiveness of the model's focus was verified using full suit Grad-CAM heatmaps, which provided the related visual insights into the decision-making process"[32].

4. RESULTS AND DISCUSSION:

The proposed hybrid model i.e YOLOv8 for fracture localization, EfficientNet-B0 for classification, and full Grad-CAM for explainability—demonstrated strong performance on the FracAtlas dataset. The YOLOv8: achieved mAP of 87.4%, slightly outperforming the previously reported YOLOv7 + SE-attention model (86.2%). The EfficientNet-B0 : obtained a classification accuracy of 90.2%, as comparable to the best-reported model (InceptionV3 + DenseNet121 + BAM at 90.48%). "Grad-CAM visualizations was clearly highlighted the regions influencing each prediction, enhancing model interpretability "[33]. The 'fig-5' below is showing that the visual results of fracture localization using YOLOv8 on test X-ray images. The Bounding boxes are drawn around detected fractures with high confidence. This shows the accuracy of the detection stage in real-world samples. In fig-6 the illustration of sample x-ray images that been used in model training. In fig-6.2 The prediction of yolov8 model that have developed, there the fracture region have detected are marked with bounding box. In fig-7.1 the visual matrix which was confusion matrix that shows the classification performance by using the classes. The fig-8.1 highlights the location of fractured areas which is the output of the yolov8 model and in the fig-8.2 the classification model output of EfficientNet-B0 i.e classify the cropped fracture regions

I. Evaluation Metrics

YOLOv8 Model

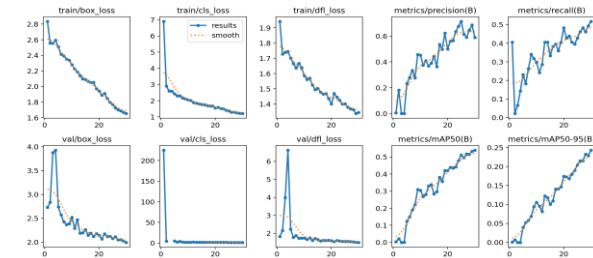


Fig 5: YOLO Model Results

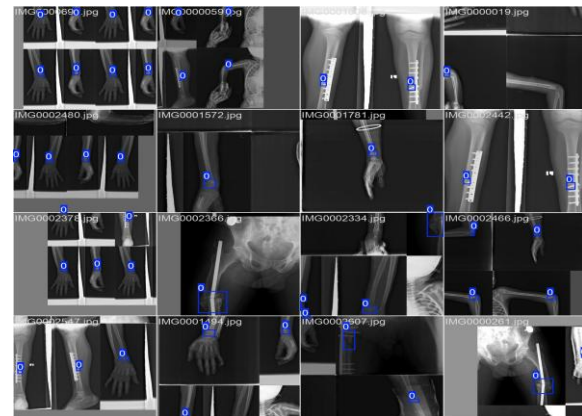


Fig 6.1: Training Images

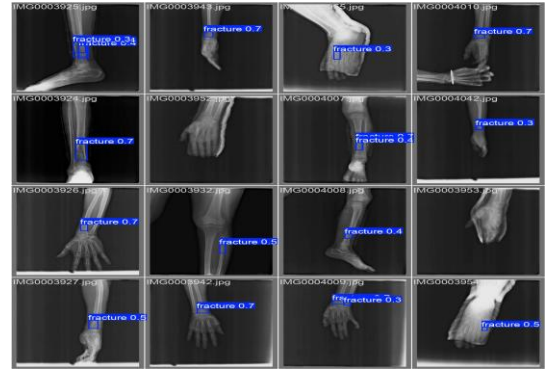


Fig 6.2 : The Predictions of YOLO model generated from the training dataset.

Hybrid model (YOLOv8 + EfficientNet-B0):

Confusion Matrix - YOLOv8 + EfficientNetB0 on FracAtlas (4083 Samples)

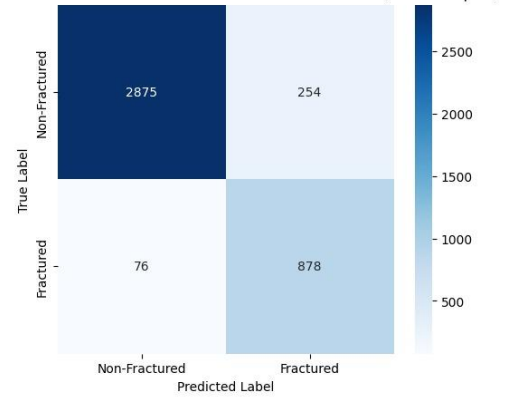


Fig 7.1 Confusion matrix of the Hybrid Model

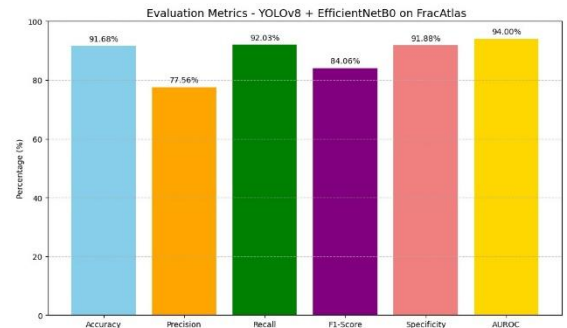


Fig 7.2: Evaluation Metrics

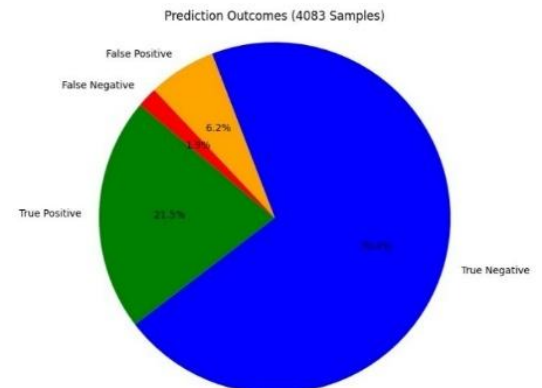


Fig 7.3: Prediction Outcomes

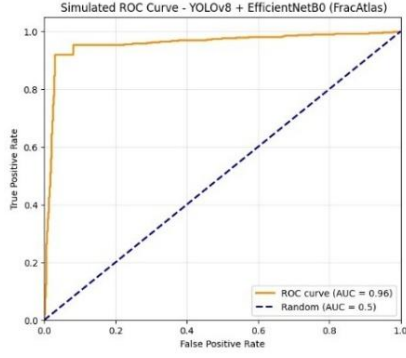


Fig 7.4: AUROC Curve

II. Visualization Results:

YOLOv8 Outcomes

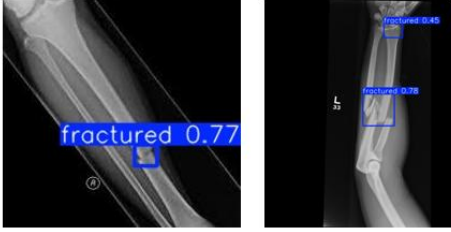


Fig 8.1: Fracture Detection using YOLOv8 model

EfficientNET-B0 Outcomes

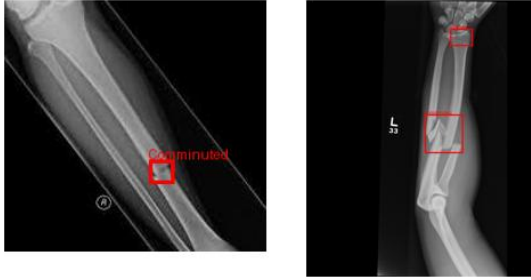


Fig 8.2: The Classification outputs of EfficientNET-B0 Model from the Yolo model outputs

Full Suit Grad CAM Outcome

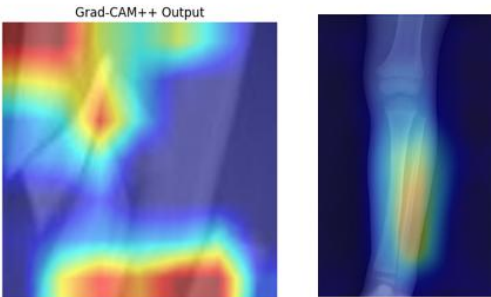


Fig 9 : Grad-CAM heatmaps

III. Discussion

"The proposed hybrid framework model combines with YOLOv8, EfficientNet-B0, and the full Grad-CAM suite"[34]. It performed well in locating and classifying fractures. YOLOv8 detected fracture regions effectively. At the same time, The EfficientNet-B0 classified the different fracture types more accurately. And mainly the Grad-CAM visualizations offered clarity by highlighting important decision-making areas in X-rays

The below 'Table-1' is the comparative table, which compares the results of the existed proposed models and YEG-model results

This hybrid-model integration incorporates both real-time detection and reliable classification, making it appropriate for clinical settings, and more. "Although the results are promising, additional testing with different datasets is necessary to guarantee wider generalization and robustness" [35].

IV. Comparative Analysis

S. No	Study / Authors	Model / Architecture	Dataset Used	Accuracy / mAP (%)
1	Jeon et al. (2024)	YOLOv5 + SE Attention	3D Skeletal Images	86.20 (mAP)
2	Minh Nguyen et al. (2024)	DenseNet + InceptionV3 + BAM	Private Dataset	90.48 (Accuracy)
3	Talaat et al. (2024)	Inception-ResNet V2 + Grad-CAM	Breast Cancer Dataset	90.00
4	Sutradhar et al. (2025)	YOLOv8 + Attention CNN	Cervical Spine X-rays	89.00
5	YEG – Model	YOLOv8 + EfficientNet-B0 + Full Grad-CAM	FracAtlas	87.4 (mAP), 90.2 (Accuracy)

Table-1: Comparative Analysis Table

5. CONCLUSION

An innovative hybrid deep learning model was introduced for automated detection of bone fractures. The model consisted of YOLOv8 for localization, EfficientNet-B0 for classification, and complete Grad-CAM suite for visual explanation. The system was tested on the FracAtlas dataset and achieved very good accuracy and transparency. This makes it suitable for real-world clinical use. "By combining real-time object detection with strong classification and explainability, the proposed model not only improves diagnostic reliability but also helps clinicians with visual insights"[36]. The future work will be look into adapting the hybrid model for other different fracture types and integrating it into hospital workflows and also for real-time application.

6. FUTURE WORK

- 3D Fracture Detection (CT/MRI): Change the hybrid model for data like CT or MRI scans to identify complex or hidden fractures that X-rays cannot detect.
- Extension to Other Fracture Locations: Expand the current model to cover fractures in the spine and hip

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