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A NEW AUGMENTATION TECHNIQUE FOR IMPROVED BONE FRACTURES IMAGE CLASSIFICATION USING YOLO

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ABSTRACT

The classification of bone fractures in medical imaging distinguishing between fractured and non-fractured bones is one of the most critical and difficult tasks. Traditional manual examination is prone to errors, especially in cases of tiny or minute fractures. Similarly, these tiny fractures are a big challenge for deep learning models, which struggle to detect and classify them effectively due to their size and variability. In this paper, we propose a new augmentation method called the Cropping Small Fracture Patches (CSFP) aimed at enhancing the representation of small fractures within training data. Our approach integrates Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance image contrast, followed by a targeted patch-based augmentation strategy that extracts small fracture regions, upscales them using Lanczos interpolation, and then combines them with original train images to enrich the dataset and used to train the YOLOv8m classification model. The proposed methodology was applied to the FracAtlas dataset and the result demonstrates a significant improvement in classification performance achieving 100% accuracy outperforming previous methods. These findings confirm the effectiveness of this approach in improving model performance; by enhancing small fracture visibility, reducing class imbalance, and improving the diversity of the dataset. However, certain limitations exist. The augmentation method relies on bounding box annotations, which may not always be available in classification datasets. Additionally, this study currently focuses on binary classification (fractured vs. non-fractured) and does not classify fracture types or anatomical locations.

KEYWORDS

Augmentation, Bone Fracture, Deep Learning, Image Classification, Preprocessing Techniques, Yolov8.

1. INTRODUCTION

Bone fractures are among the most common injuries that affect the lives of people. These types of injuries usually occur because of accidents, such as falls or traffic accidents, or due to osteoporosis, especially among older individuals (Meena and Roy, 2022). The ability to diagnose and classify these fractures quickly and accurately is critical for proper treatment planning and the minimization of those risks associated with injury and permanent deformity. The diagnostic procedures have relied heavily on human expertise in analyzing X-ray images, which are one of the most important diagnostic tools in determining whether a fracture exists. This requires great precision and long experience to avoid mistakes. However, as the number of images processed daily increases, doctors encounter several challenges in diagnosing fractures, including the identification of hidden fractures among complex details in medical images. Moreover, fatigue or time pressure at work may increase the rate of error and thus deteriorate diagnostic quality, putting the lives of patients in danger (Kraus et al., 2024).

With the rapid progress of artificial intelligence technologies, systems supported by deep learning have become an effective tool in medical image analysis, as convolutional neural network (CNN) algorithms extract fine features from images with high accuracy (Mohammed et al., 2022), making them ideal for classifying medical images, including bone fracture images. These systems contribute to innovative solutions for better accuracy and speed of diagnosis, hence improving healthcare quality (Joshi and Singh, 2020). However, these systems still face significant challenges, especially when small or fine-detailed bone fractures are concerned. Applying network operations such as pooling layers to reduce the dimensions of data may result in the loss of some important details relating to small fractures, thus negatively impacting classification accuracy. On the other hand, fractures have large variability in shape, location, and quality; this creates huge variability in the images, thereby making it harder to train the model to distinguish between them (Kutbi, 2024).

Recently, several models have been proposed that are based on various strategies, such as transfer learning and image tiling approaches (Unel, Ozkalayci and Cigla, 2019), to improve the representation of small objects. Improving the representation of small fractures and increasing model focus toward the region of interest, leads to more accurate and faster results, hence helping clinicians make better diagnostic decisions. In this paper, we propose an approach for classifying X-ray images into two classes: images with and without fractures. This approach is based on a new augmentation technique that will improve the representation of small fractures in the training dataset, hence improving the performance of the model used. We also rely on the robustness of the YOLOv8m model due to its ability to effectively handle small and fine-detailed features, which are crucial for accurate fracture classification. However, existing methods face limitations in detecting small and fine fractures, as conventional deep-learning architectures often lose critical details during feature extraction. Additionally, the imbalance between fractured and non-fractured samples in datasets can bias models toward the majority class, reducing sensitivity to fractures. These challenges highlight the need for an approach that enhances small fracture representation and improves dataset balance, ensuring better generalization and diagnostic accuracy. This study contributes to enhancing AI-based fracture classification which can support radiologists in making more accurate and efficient diagnostic assessments.

2. RELATED WORK

This section presents related past work to this research in two aspects. First, it highlights and emphasizes the applicability and efficiency of methodologies and techniques for tackling the challenges in the detection of small-size objects. Then, previous works on datasets used in this work, which is the FracAtlas dataset (Abedeen et al., 2023), are considered to provide a comparison with our proposed approach.

Researchers (Kisantal et al., 2019) propose two ways to deal with the scarcity of images of small objects, namely oversampling and copy-paste, adopting a copy-paste strategy that takes the detected or illustrated States of small objects from different images. Then they are copied and pasted on other background areas in the selected training images. This is done in an attempt to amplify the presence of small existing categories of objects artificially, the Mask-RCNN is retrained, and it was found that this method improved by 7 percent over the original results obtained using the same model.

The authors (Akyon et al., 2022) introduced the Slicing-Aided Hyper Inference (SAHI) framework, which segments images into smaller overlapping tiles, with tile size and overlap ratio decided by the user. A detection model is applied to each tile, and the resulting detections from all tiles are aggregated into the original image. This approach showed strong effectiveness in detecting small objects, achieving an AP50 score of 43.5 on the VisDrone2019 dataset.

The study by (Chen et al., 2024) introduces an enhanced Weighted-Channel-Attention YOLO model for detecting bone fractures in radiographic images. It incorporates the DSC-C2f module, replacing the standard C2f in YOLOv8, and the WCA mechanism to improve focus on abnormal regions. Testing on the FracAtlas dataset demonstrated a mAP of 56.7, marking an 8.8% improvement.

The study by (Akhlaq et al., 2024) explores bone deformity analysis using YOLOv8 models combined with interpretable AI (XAI) techniques on the FracAtlas dataset. EigenCAM is utilized to generate heat maps, revealing the decision-making process of the YOLOv8m model, which achieved a mAP@0.5 of 59.5% for fracture detection and 83.1% for binary classification. Additionally, YOLOv8s demonstrated remarkable performance in multiclass classification, achieving 96.2% accuracy in identifying fractures by anatomic region.

The study by (Alshahrani and Alsairafi, 2024) investigates deep learning-based bone fracture classification using the FracAtlas dataset. It compares the performance of YOLOv8 and VGG16 models, revealing that YOLOv8 achieved an accuracy of 80% after 50 epochs, significantly outperforming VGG16, which attained 73.01% test accuracy.

The authors (Ruhi et al., 2024) introduce a bone fracture classification model leveraging transfer learning with the InceptionV3 architecture enhanced by Bottleneck Attention Modules (BAM). These modules improve model performance by emphasizing fine fracture regions. Experiments on the FracAtlas dataset demonstrated a classification accuracy exceeding 90%.

Previous studies have demonstrated notable advancements in deep learning models for the fracture classification task from medical images. However, they still face several limitations. Many existing methods struggle with detecting small and fine fractures, as conventional deep learning architectures often lose critical details during feature extraction and pooling operations. Additionally, some studies have attempted data augmentation, but they often apply generic transformations that do not specifically enhance the visibility of small fractures. These limitations highlight the need for a more targeted approach that enhances small fracture representation and improves dataset balance, ensuring better generalization and classification performance. In this work, a new approach is presented focusing on improving the representation of small fractures. By refined training data and improving model focus on those crucial areas, may increase the accuracy and efficiency of the classification.

3. DATASET DESCRIPTION

FracAtlas dataset is used in this work, which is designed to support studies related to diagnosis regarding bone fractures using radiographic images. The dataset was collected from three different hospitals in Bangladesh, containing 4083 radiographic images. 717 of the images contain fractures of different types including hand, shoulder, hip, and leg, whereas 3363 images do not have any fractures, thus resulting in the problem of class imbalance for the non-fracture class, that might bring a significant challenge for machine learning models because the models may tend towards biased predictions towards the most representative class. The annotations process involved two radiologists and an orthopedist, where fracture locations were identified using bounding box coordinates. FracAtlas supports multiple formats such as COCO, VGG, YOLO, and Pascal VOC making it a versatile tool for deep learning applications in fracture detection, classification, and segmentation.

4. METHODOLOGY

4.1. Preprocessing

As a preprocessing step, first corrupted images were removed from the dataset to ensure training quality and then the Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to address the problem of low-contrast images, hence improving the quality of the input data for the model (Musa, Rafi and Lamsani, 2018). This approach enhances image contrast while limiting noise amplification and maintaining fine details, making it suitable for medical applications that require accuracy and clarity (Hayati et al., 2023). CLAHE is applied to enhance the clarity of features, such as important regions or small fractures, which might be ambiguous in the original images; hence, it makes the models recognize fine patterns better and achieve higher performance, which facilitates the image classification process. Fig. 1 shows an example of a photo before and after applying this technique. After that, the dataset was split into three subsets: 75% training, 15% validation, and 10% testing. Consequently, the number of images in each set became as illustrated in Table 1.

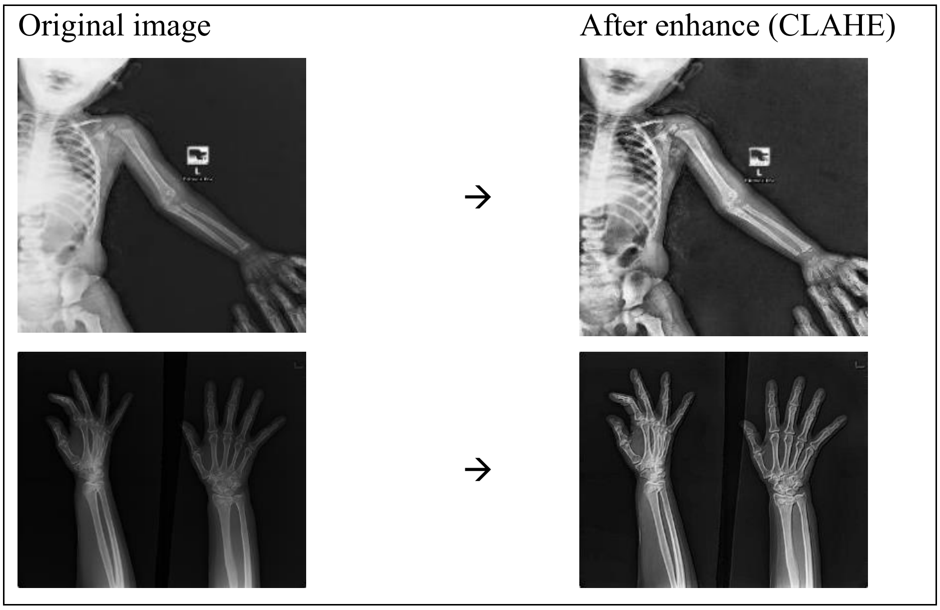

Fig. 1. shows an example of images before and after applying CLAHE.

Table 1.Shows the number of images in train, valid, and test sets,

subsets	Fractured	Non-fractured
Train	539	2459
Val	107	492
Test	71	328

4.2. Proposed Method: Cropping Small Fracture Patches (CSFP)

Data augmentation is the process of artificially increasing the number of samples in a dataset with modified versions of the same data. It may include flipping, rotating, scaling, and changing brightness or contrast of the X-ray images, among other techniques (Mumuni and Mumuni, 2022). In this work the CSFP approach aims to enhance the performance of small fracture classification in medical images by applying a new augmentation technique in a way that depends on cropping small parts (Patches) of the image specifically around the small objects (fractures). In contrast to traditional methods that rely on processing the entire image or making random splits, patches around small fractions are cropped based on the Bounding Box coordinates provided in the dataset, to improve their representation during the training process. The steps for how this method works are shown next in details:

1. Step 1: Small Object Identification and Patch Creation: A small object is defined as having Bounding Box dimensions (width and height) less than or equal to 20% of the original image dimensions. Based on this definition, a 500×500-pixel patch is cropped around the Bounding Box of the small objects in the input image while ensuring the object is at the center of the patch. The patches ensure that the object with its very immediate surrounding context is totally encompassed to capture any critical details and allow concentrated attention on the region of interest without losing essential information concerning the fracture.
2. Step 2: Up-sampling with Lanczos Interpolation: Up-sampling is the process that increases the size of an image by interpolating new pixels based on already existing ones. This step is very important particularly when conforming images to the input requirements of machine learning models, as preserving critical features improves model performance (Sales et al., 2023). In this work, the extracted patch is up-sampling by the Lanczos interpolation technique to the desired input size of the model, this technique is one of the most effective in medical imaging, as it enhances the clarity of images without losing important details. Lanczos interpolation was chosen because it maintains the fine details of small objects; unlike simpler interpolation techniques, such as nearest neighbor or bilinear interpolation, Lanczos minimizes distortion or loss of information; hence, it presents the best option when medical images are concerned (Azam et al., 2022). The Lanczos method uses a dilated sinc filter, which minimizes distortions by balancing sharpness and smoothness during resizing. The Lanczos filter is mathematically defined as:

$$sinc(k) = \begin{cases} 1, & for\ k = 0 \\ sin(\pi k/n)/(\pi k/n), & otherwise \end{cases} \quad (1)$$

Where k is the region kernel on the original image and n is the order of the function and controls the kernel size of the filter. This is a relatively safe approach since no important information about the fracture would be lost in the resizing process. Through the use of Lanczos interpolation, the details of fine fractures are preserved in the patches after resizing; hence, ideally used in tasks that require high precision like fracture classification in X-ray images (Moraes et al., 2020).

3. Step 3: Integrating Patches into the Training Dataset :The generated Patches are combined with the original training dataset, which enhances the representation of small fractions in the training data. Through the use of this approach, an additional 638 Patches were produced and combined with the initial training set of 539 images, resulting in a dataset of 1177 images in total. This expanded data set improves the generalizability of the model and increases its effectiveness in determining exact fractions. Fig. 2 shows an example of the workflow of the proposed method.

The advantages of the proposed approach:

- Improve model focus: By focusing on small fractures rather than the full image, this approach enhances the capability of the model to identify and handle fine features, as it focuses on the regions of interest.
- Improve dataset effectiveness: Merging patches into the original images increases the training dataset, adds variety, and reduces the imbalance between the two classes of fracture and non-fracture represented in the images. This generally enhances the effectiveness of training the model for its intended purposes and enables the model to perform better in unfamiliar situations.

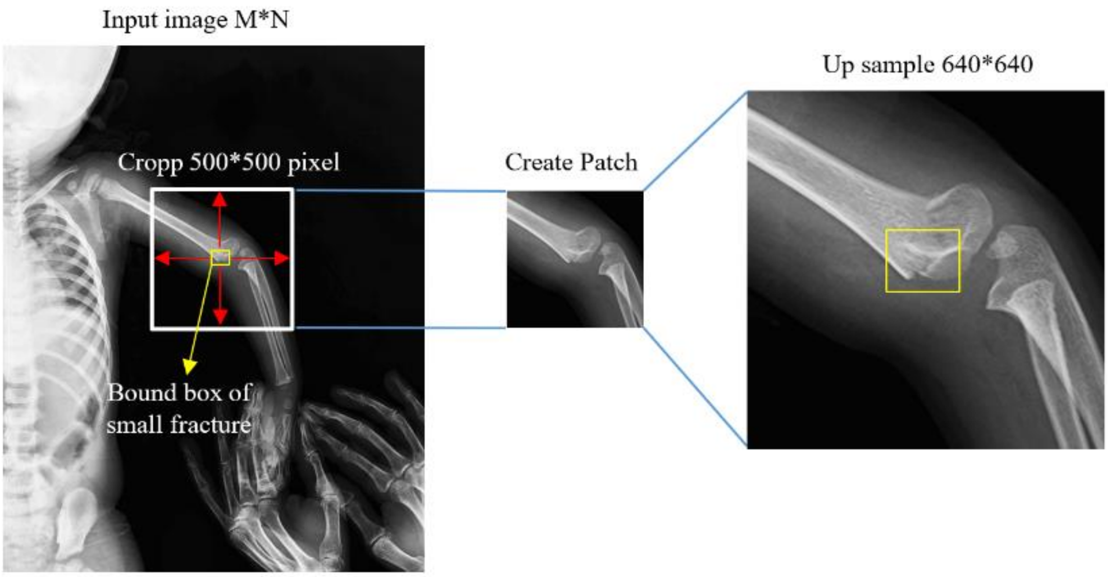

Fig. 2. The proposed method works, where the yellow square represents a ground truth of the small fracture.

4.3. Model Architecture

Once the augmented dataset is prepared, the next step is to train the YOLO (you only look once) model and evaluate its performance. The YOLOv8m model was selected because of its good balance between detection accuracy and computational efficiency. It was implemented in this work without any changes in architecture to evaluate the effectiveness of the proposed CSFP method and thus provide a comparison with earlier related research works. YOLOv8 is the upgraded version of the YOLO series of models developed by Ultralytics in the year 2023 (Alaa et al., 2024). The model has employed CSPDarknet as its backbone, using Cross-Stage Partial Networking to optimize the feature extraction process while trying to reduce computational overhead. Thus, YOLOv8 can balance accuracy and computational efficiency, enabling fast processing of images without losing performance. Also, in YOLOv8, PANet (Path Aggregation Network) was added into the middle layers for easy flow and fusion of features at various levels of the network (Sohan et al., 2024). PANet added one more pathway, improving the relationship between the ascending and descending pathways and thereby enhancing its object recognition capability of diversities of size and dimensions. This particular aspect is crucially critical in the analysis of medical images, where small entities such as fractures may appear in variable scales and orientations.

Another essential feature of YOLOv8 is being anchor-free, avoiding dependence on pre-defined reference boxes, which takes the network to even more simplification and increases the accuracy for small and packed objects (Terven and Cordova-Esparza, 2023). Besides, advanced loss function, including Binary Cross-Entropy for classification is used in YOLOv8 (Hussain, 2024). These enhancements make YOLOv8 particularly well-suited for detecting fine-grained details like subtle fractures in medical images. Fig.3 illustrates the architecture of the YOLOv8 model.

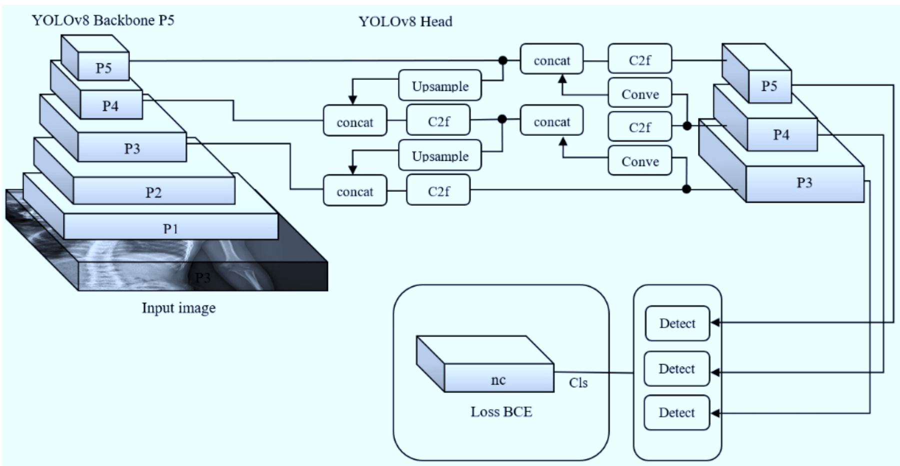

Fig. 3. The architecture of the YOLOv8 model.

Fig.4 shows, in summary, a block diagram of the methodology pursued in this work. It describes the main steps, starting from a preprocessing step to enhance image quality, passing through the proposed CSFP method to adapt to the small object representation problems, and ending with the YOLOv8 model training and evaluation steps to assess its performance in classifying a medical image as fractured or non-fractured.

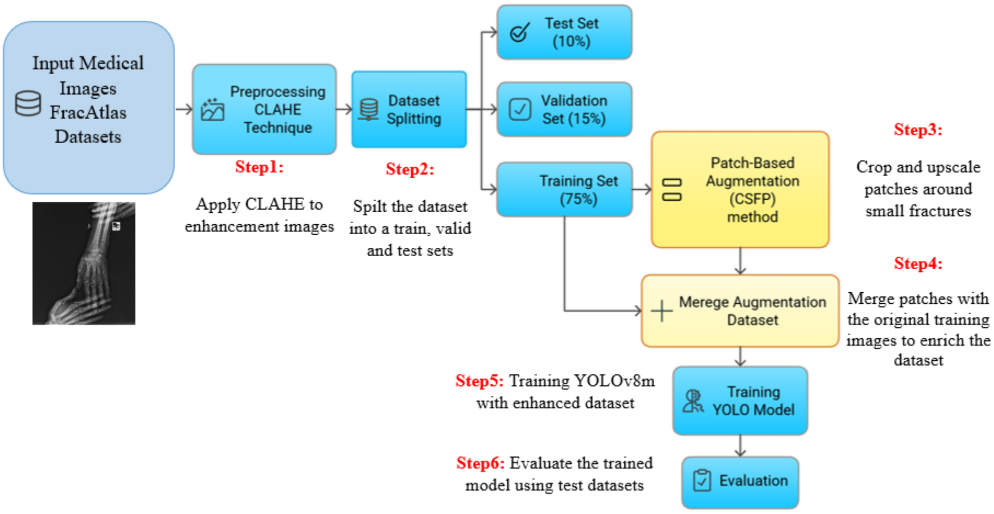

Fig. 4. Block diagram illustrating the workflow of the proposed methodology.

5. EXPERIMENTAL SETUP

5.1. Experimental Platform

In the local computer, data preprocessing was done. CLAHE was used for image enhancement, the proposed method was implemented, and images were prepared for training. The model training was made on the Google Colab platform to take advantage of the T4 GPU, which provides 12.7 GB of system memory (RAM) and 15.0 GB of GPU memory. To train the model, the Ultralytics library was used for the implementation of the YOLOv8m model for classification task. The training process was completed within 0.757 hours after executing 25 iterations (Epochs) due to early stopping. The experiment included setting the following parameters for classification tasks to improve performance:

- Learning Rate: 0.0001
- Batch Size: 8
- Optimizer Algorithm: Adam
- Momentum: 0.937
- Image Size: 640

5.1 Evaluation Metrics

Performance was measured over a series of performance metrics common to the tasks of classification (Padilla et al., n.d.). (Sivalingan, 2024)That is:

1) Accuracy: Used to evaluate how well the model correctly classified the samples. It is calculated as:

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{True Negative} + \text{False Negative}} \quad (2)$$

2) Precision (P): The ratio of correct predicted returned by the model to the total number of predict. It is computed as follows:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (3)$$

3) Recall: The ratio between correct predictions and the total number of positive samples It is computed as follows:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (4)$$

6. THE RESULT AND DISCUSSION

As shown in Fig. 5, The proposed approach demonstrated effective performance in distinguishing between fractured and non-fractured images. The model achieved 100% accuracy on the test set, indicating effective classification within the given dataset. Table 2 compares the performance of the current model with the performance of models used in previous research, confirming the superiority of the proposed method. Fig. 6 shows the confusion matrix of the classification test and Fig. 7 shows examples of fracture classification during the test process.

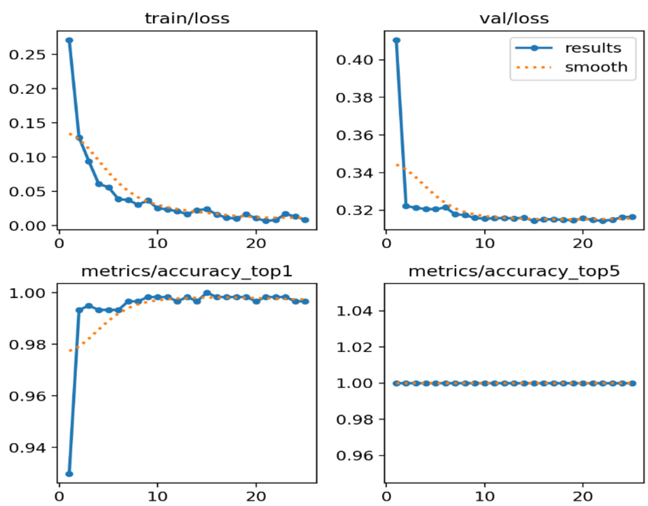

Fig.5. performance of the model for fracture classification task during the training process.

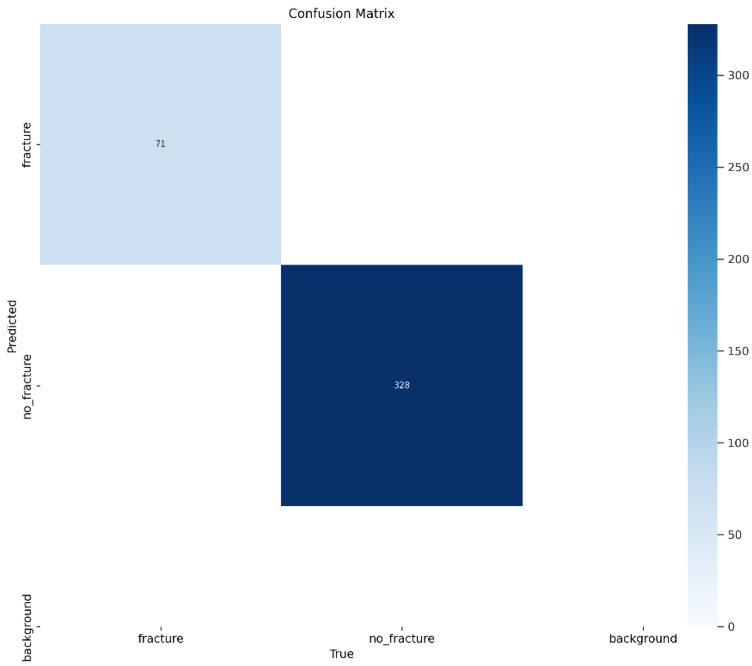

Fig. 6. Confusion matrix of the classification of the fracture during the testing process.

Table 2. Comparison of the performance metrics of studies for fracture classification on the fracatlas dataset.

Source	Method	Accuracy
(Akhlaq et al., 2024)	EigenCAM+YOLOV8m	83.1%
(Alshahrani and Alsairafi, 2024)	Data augmentation + YOLOV8	81%
(Ruhi et al., 2024)	InceptionV3 + BAM	91.3%
(Bhuiyan et al., 2024)	DenseNet121 + tailor-made layers	93%
(Gupta and Sharma, 2024)	Data augmentation + EfficientNet	96.83%
ours	CSFP +YOLOV8m	100%

a) Ground truth

b) predicted

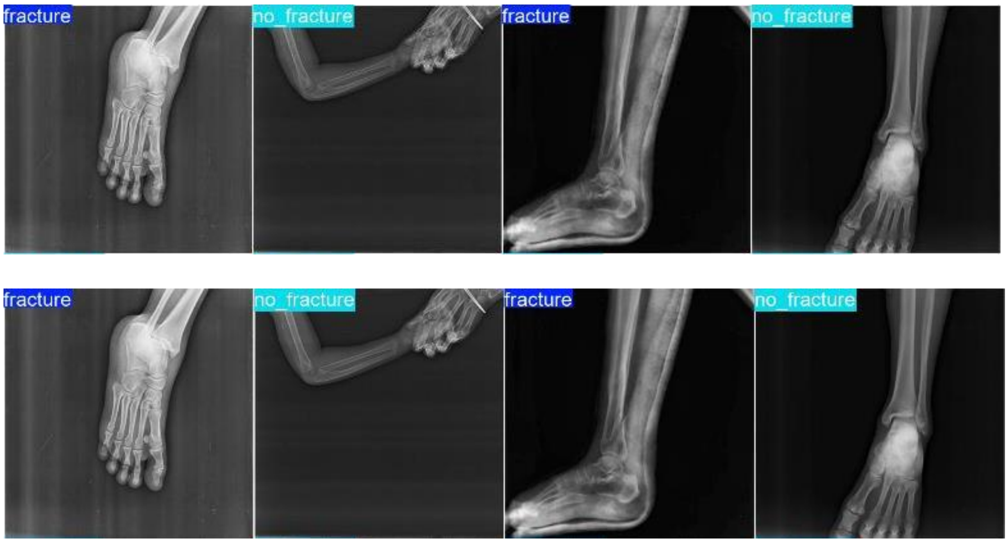

Fig. 7. Examples of fracture prediction during the test process. (a) represent ground truth images and (b)represent predicted images.

To provide a more detailed evaluation, we also calculated Precision and Recall. Since the model achieved effective classification, these metrics are also at their good values:

- Precision = 100% (All predicted fractures are correctly classified).
- Recall = 100% (All actual fractures are identified).

The results of this study demonstrate the effectiveness of the proposed approach in improving the classification of bone fracture images. The proposed methodology overcomes critical limitations regarding the classification methodologies used by previous studies. Unlike previous methods that rely on raw images, our preprocessing step using CLAHE enhances image clarity while mitigating noise amplification. By applying CLAHE, the model can better distinguish fracture regions, leading to improved feature extraction. Additionally, the CSFP augmentation method directly addresses the challenge of class imbalance, where in the original dataset, non-fractured images significantly outnumber fractured images, leading to biasing the model toward the majority class. Our method counteracts this by generating additional samples of fracture images, ensuring a more balanced dataset. Enriching the dataset with targeted patches focusing on small fractures has improved their representation, which can contribute to better generalization of the model. The classification results show effective model performance, where the accuracy stands at 100%, and therefore prove the efficacy of the proposed method in enhancing training data quality and giving the model an discrimination capability between fracture and non-fracture images. This further ensures that the method is performing well in making the focus of the model on areas of interest, hence assuring that small fraction details will be well represented during training.

7. FUTURE WORK

Building on these promising results of this work, several research could be explored in extending the proposed methodology to maximize its utility and impact. Currently, only binary classification for the presence and absence of fractures is considered within the approach. Extending the method into multiclass classification tasks, such as categorizing the type of fracture or location, will provide more specific diagnostic outputs. Integration of this system into real-time diagnostic systems may render the method practical for clinical applications, especially in time-sensitive environments. Finally, an adaptation of the methodology to other challenges in medical imaging, such as tumor detection, can be done to assess the applicability of the approach in healthcare. These directions go toward refining and extending the impact of the approach to better diagnostic tools.

8. CONCLUSION

The present research work introduces the Cropping Small Fracture Patches (CSFP) augmentation method, designed to enhance the representation of small fractures in medical image classification. The proposed methodology is effective in addressing the difficulty of distinguishing fine details in fractures and issues concerning imbalanced datasets. By creating rich-context patches around these minimal fractures and augmenting them to the training set. The proposed approach integrated with the YOLOv8m model, demonstrated effective classification performance achieving 100% accuracy on the test set of the FracAtlas dataset. These results bring out the robustness of the proposed method in enhancing data quality and improving the capability of the model to differentiate between fractured and non-fractured images, thus being an important step toward better AI-powered medical practices, which helps improve diagnostic accuracy and reduces potential errors.

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