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Research Article

Bone fracture detection using image processing techniques

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ABSTRACT

Bone fractures are common injuries that need timely and accurate diagnosis. Conventional diagnostic procedures, such as X-ray imaging, are critical in finding fractures, but they usually depend on manual interpretation, which can lead to human errors and inefficiency. To solve these issues, our study intends to create an automated method for detecting bone fractures using machine learning and image processing. This method consists of several phases, including feature extraction, edge detection, pre-processing, as well as machine learning categorization. In addition to identifying the existence of a broken bone in X-ray pictures, this system will label the position of several fracture types within the image. To achieve high accuracy, a modern object recognition algorithm is trained using a collection of X-ray pictures. By uploading their x-ray photos to the platform, customers will be able to examine and detect fractures remotely thanks to a website that has been built. The model achieved an accuracy of 76% and processed images at an average speed of 30 ms per image.

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INTRODUCTION

X-ray imaging is a widely utilized technique in the medical field for the diagnosis of various medical conditions, including bone fractures, lung diseases, and tumours. However, the interpretation of X-ray images can be a complex and time-consuming task, particularly for radiologists who lack experience or are burdened with heavy workloads. Consequently, there is a pressing need to expand computerized and precise methods for X-ray examination that can assist healthcare professionals and enhance patient outcomes.

In the pursuit of this goal, prior studies have made notable contributions in the field. For instance, in reference [1], highlights that the Support Vector Machine (SVM) algorithm achieved the highest accuracy in their research. Additionally, Sreelakshmi [2] investigated using MATLAB 7.8.0 as an application package for images capturing, processing, and UI enhancement, whereas Rajesh Raman and associates [3] achieved a respectable 85% level of accuracy

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in bone fracture detection. 10 deep learning algorithms were employed in their investigation to identify fractures, and the outcomes were then compared. Various augmentation techniques were tested, and the most suitable method for X-ray images was identified [4].

In developed regions, experienced radiologists accurately interpret X-ray images, while smaller hospitals in underdeveloped areas may lack skilled surgeons [5]. This shortage of radiologists can delay patient care, impacting surgical success rates. Recent studies show a 26% increase in misinterpreted X-ray images [6]. In recent times, object detection models have gained significant attention and have been increasingly utilized for fracture detection [7], a widely explored subject in the realm of computer vision (CV) [8]. In the field of object detection, deep learning techniques have become the leading approach. These methods utilize neural networks to automatically learn and extract features from images, enabling precise identification of objects, including fractures [9]. Deep learning methods can be categorized into two-stage and one-stage algorithms. In the case of two-stage algorithms [9,10], exemplified by R-CNN and The odds of its variations, location, and class are determined in two steps. On the other hand, one-stage techniques generate these probabilities immediately, improving the speed of model inference [11,12].

In this research, we used the GRAZPEDWRI-DX dataset to instruct the model through the YOLOv8 method. Then, based on experimental data, a comparative study was conducted with different models [13], and the results showed that our model had the greatest mean average accuracy (mAP 50) as well as F1 score value.

Inspired to develop a strong deep learning framework built around YOLOv8 that can locate fractures in bones within x-ray pictures, we suggest a website that allows users to view and diagnose fractures from a distance. Our work's primary contributions may be summed up as follows:

The main goal of this Endeavour is to develop the model that can recognize fractures in x-ray pictures. The main objective is to reduce the possibility of mistakes during X-ray image interpretation by helping surgeons analyze X-ray pictures on their own.

The YOLOv8 model is now performing better than before. Based on the GRAZPEDWRI-DX dataset, our model has the greatest average mean accuracy in fracture identification, according to the experiment findings. Finally, we created a website that enables customers to upload their x-ray pictures to the platform and remotely see and locate fractures in those photos. The aim of the present work is to Develop a robust and efficient model for bone fracture detection using YOLOv8 aims to significantly enhance accuracy compared to existing methods. This involves close collaboration with medical professionals to ensure the system's clinical relevance and practicality. The goal is to accurately identify various types of bone fractures from X-ray images using a trained deep learning model, ensuring the model's broad applicability across multiple body parts and diverse medical scenarios. Additionally, a user-friendly web application will be designed to allow medical professionals and users to remotely access and detect fractures in X-ray images with ease, thereby improving accessibility and convenience in fracture diagnosis2.

Literature Survey

The study aims to propose a system using x-ray images to identify hand bone fractures quickly and accurately [15]. The system detects and classifies fractures using machine learning and image processing techniques. It uses supervised learning with labelled examples of transverse and oblique fractures to classify instances [14]. The system starts by collecting labelled x-ray hand images, including both normal and fractured hands. These images are filtered to reduce noise and edge detection methods are used to identify the edges. The images are then transformed into features. Classification algorithms are created based on these features. The system's effectiveness and precision are evaluated through testing procedures. T.K. Hazra and S. Dutta proposed a method for classifying bone fractures based on GLCM values and other features, achieving algorithmic accuracy [16].The latest in the YOLO series, YOLO (V7), significantly improves detection speed and accuracy, with E-ELAN recommended for enhancing learning capacity [17]. The two primary stages of the method that Kamil Dimililer suggested are processing and categorization. During the processing stage, fracture areas and improve picture quality using methods like SIFT feature extraction and Haar Wavelet transformations. Matlab is employed for system implementation and simulation [18]. In x-ray pictures, broken bones are identified faster using RCNN and then classified using a more precise identification method [19].

Rui-Yang Ju and Weiming Cai present a way to use data enhancement on the original data set to improve the YOLOv8 model's performance [20]. Hang Min and his colleagues work explores the feasibility of Deep Learning (DL) for Distal Radius Fracture (DRF) classification but notes limitations due to small datasets and inter-observer variance [21]. Although DL algorithms perform on par with physicians, there are still issues with their clinical application. These can be resolved by using sophisticated visualization techniques, comprehensive clinical data interpreting, treatment suggestions, and enhanced interpretability [22]. FPNs are commonly employed to address variance in object sizes utilizing several layers of feature maps in identifying objects, especially crack detection in PXR. We also explore the 'Bag-of-words' model for picture classification and Haralick's statistical equations for texture description [23-25]. On the other hand, not much research has been done on using the YOLO model to identify fractures. This study uses the technique that Ultralytics announced in 2023 to train the model in order to detect fractures in x-ray pictures [26].

MATERIALS AND METHODS

In this work, we use the You Only Look Once (YOLO) object identification framework to accurately identify fractured bones in x-ray pictures by their specific location and position. By utilizing Yolov8's enhanced accuracy in object recognition and localization tasks, we want to significantly improve medical imaging processes and raise the bar for fracture diagnosis in medical pictures. YOLO v8 Modified Architecture as shown in figure 1.

Dataset

The Medical School at the University of Graz has made available the GRAZPEDWRI-DX dataset, It comprises 20,327 X-ray pictures of pediatric wrist injuries. Several pediatric radiologists from University Medical Institute Graz's Institute for Orthopaedic Surgery gathered these pictures during a ten-year period, from 2008 to 2018. The dataset, which has bounding boxes added to the photographs to represent different circumstances, is annotated in nine different classifications and is available to the public [27].

Data Augmentation

To increase the size of our dataset throughout the model-training process, we used data augmentation approaches. Specifically, we manipulated in the original X-ray images' contrast and brightness to enhance the visibility of bone anomalies.

YOLOv8 Representation

YOLOv8 served as an initial model for our investigation. The most recent model in the YOLO lineup of real-time image detection systems, YOLOv8, offers cutting-edge precision and quickness. YOLOv8 is an excellent choice for detecting fractures of bones in x-ray pictures since it builds on the advances achieved in previous versions of YOLO and adds new features and improvements.

YOLOv8 incorporates the latest designs in backbone and neck architectures, enhancing its ability to extract features and detect objects. Compared to conventional anchor-based techniques, the model's anchor-free splits Ultralytics head improves accuracy and streamlines the detection process [28]. YOLOv8 is perfect for real-time object identification in a variety of applications since it is designed to balance processing speed and precision. With YOLOv8, a variety of pre-trained models are offered, offering customized solutions for various jobs and performance requirements. The four key parts of the YOLOv8 algorithm's architecture are the lost function, neck region, the head, and backbone:

Backbone

In YOLOv8 model it uses a customized version of the CSPDarknet53 architecture as its backbone. The primary job of the backbone is to extract significant characteristics from the input image [29]. It does this by identifying basic patterns in the initial layers and adjusting to different scales of representation as the network progresses. This hierarchical representation is crucial for accurate object detection.

Neck

The neck is a crucial link connecting the backbone and head, performing feature fusion, integrating contextual information, and reducing dimensionality. It combines features from different scales, improves object detection at varying resolutions, considers broader scene context, and reduces data resolution and dimensionality for faster computation. However, this reduction may affect the model's quality [30].

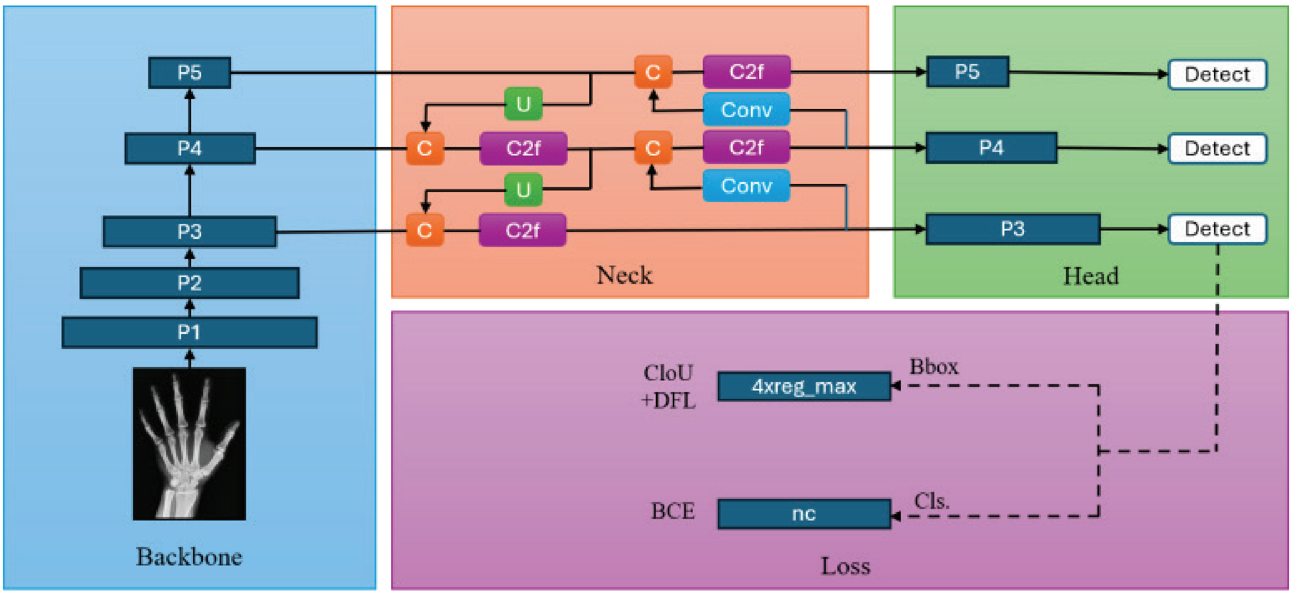

Figure 1. YOLO v8 modified architecture.

Head

The YOLOv8 network's final component is the head, which produces bounding boxes, confidence scores, and object categories for identified objects. The head generates bounding boxes for potential objects, assigns confidence scores to each box, and categorizes the objects based on their respective categories. This enables the identification of specific objects within the scene [31].

YOLOv8 is a single-stage object detector that consists of three main components: backbone, neck, and head. The backbone is a convolutional neural network that extracts features from the input image. The neck is a collection of neural network layers that combines and mixes features to pass it to the next stage for prediction. The head is the final output layer that consumes features from the neck and creates prediction outputs.

- **Backbone:** In YOLOv8, the backbone serves as a critical component responsible for extracting features from input images. YOLOv8 employs ResNeXt as its backbone architecture, a cutting-edge convolutional neural network (CNN) design that builds upon the foundation of ResNet. ResNeXt introduces innovative enhancements to the traditional ResNet architecture, primarily through the implementation of grouped convolutions and a split-transform-merge strategy. Grouped convolutions allow ResNeXt to divide the input channels into multiple groups and perform convolutions independently within each group. This strategy facilitates richer feature representations by encouraging diverse feature learning across different groups. The split-transform-merge strategy employed by ResNeXt involves splitting the input feature maps into smaller subsets, transforming them through separate pathways, and then merging the transformed features back together. This approach enhances feature diversity and encourages cross-channel interactions, leading to more expressive feature representations. Importantly, ResNeXt achieves these improvements in model capacity and generalization capabilities without significantly increasing computational complexity. By leveraging grouped convolutions and the split-transform-merge strategy, ResNeXt enhances feature extraction efficiency and enables the backbone to capture more discriminative features from input images.
- **Neck:** In YOLOv8, the neck plays a pivotal role as an intermediary between the backbone and the head, facilitating seamless information flow and enhancing the model's capabilities. Employing the Spatial Pyramid Pooling Fusion (SPPF) structure, the neck in YOLOv8 is designed to perform several essential tasks.
- **Feature fusion:** One of the primary functions of the neck is to merge features from multiple scales. By integrating features extracted at different spatial resolutions, YOLOv8 can effectively detect objects of varying sizes within the input images. This feature fusion process enables the model to maintain robustness across a wide range of object scales, enhancing its overall detection performance.
- **Contextual information:** Another critical task of the neck is to incorporate contextual information from the surrounding scene. By considering the broader context in which objects are situated, the neck enhances the model's understanding of the scene, leading to more accurate and contextually informed object detection. This contextual awareness enables YOLOv8 to make more informed decisions when identifying and localizing objects within complex scenes.
- **Dimensionality reduction:** While maintaining computational efficiency, the neck in YOLOv8 performs dimensionality reduction on the fused features. By reducing the spatial resolution of the feature maps, the neck effectively compresses the information while preserving essential semantic details. This dimensionality reduction process optimizes computational resources and facilitates efficient processing of features during subsequent stages of the model.
- **Head:** In YOLOv8, the head serves as the final stage of the object detection pipeline, responsible for producing the model's ultimate predictions. Comprising multiple convolutional layers followed by fully connected layers, the head operates on the fused features provided by the neck to generate the final output. This component of the model performs several crucial functions:
- **Bounding Box Prediction:** The head predicts bounding boxes that delineate the spatial extent of detected objects within the input image. These bounding boxes define the regions of interest where objects are localized.
- **Confidence Score Assignment:** For each predicted bounding box, the head assigns a confidence score that reflects the model's confidence in the accuracy of the prediction. This score indicates the likelihood that the predicted bounding box contains a valid object.
- **Object Categorization:** Additionally, the head categorizes detected objects into specific classes or categories, such as "person," "car," or "dog." This classification step enables YOLOv8 to provide not only the location of objects but also their semantic labels.
- **Loss:** In YOLOv8, the loss function plays a crucial role in guiding the training process by quantifying the disparity between predicted values generated by the model and the ground truth annotations associated with the training data. YOLOv8 employs a combination of loss terms to effectively train the model:
- **Localization loss:** This loss term evaluates the accuracy of the bounding box predictions made by the model. It measures the discrepancy between the predicted bounding box coordinates and the ground truth bounding box coordinates, thereby guiding the model to accurately localize objects within the input image.
- **Confidence loss:** The confidence loss assesses the confidence scores assigned to the predicted bounding boxes. It quantifies the model's certainty or confidence in its predictions, penalizing inaccurate confidence scores and encouraging the model to assign higher confidence

to accurate detections while penalizing false positives and false negatives.

- **Class loss:** This component of the loss function ensures the accurate classification of detected objects. It measures the disparity between the predicted class probabilities and the ground truth class labels associated with each bounding box. By penalizing misclassifications and encouraging correct classifications, the class loss term guides the model to accurately identify the semantic labels of detected objects.

The overall loss used in YOLOv8 training is a weighted sum of these individual loss components. By combining localization, confidence, and class losses in a weighted manner, YOLOv8 optimizes the model parameters during training to minimize the overall loss and improve its performance in object detection tasks.

The Medical University of Graz has released the GRAZPEDWRI-DX37 dataset, consisting of 20,327 X-ray images depicting wrist trauma in pediatric patients. These images were collected over a decade, from 2008 to 2018, by a team of pediatric radiologists at the Department of Pediatric Surgery in the University Hospital Graz. All radiographs have been de-identified, and the DICOM pixel data has been converted to 16-Bit grayscale PNG images. The filenames and accompanying text files provide basic patient information such as age and sex. Multiple pediatric radiologists annotated the dataset images by delineating pathologies like fractures or periosteal reactions using lines, bounding boxes, or polygons, as well as tagging general

Figure 2. X-ray images for experimentation.

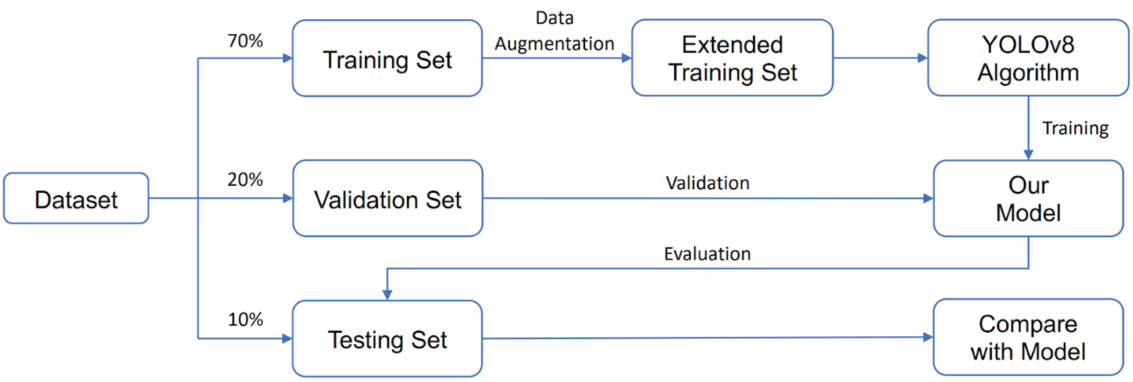

Figure 3. Algorithm for experimentation.

image characteristics. The dataset is meticulously categorized into nine distinct classes, with bounding boxes outlining the regions of interest.

We randomly segment the GRAZPEDWRI-DX dataset into three subsets: a training set, a validation set, and a test set, constituting roughly 70%, 20%, and 10% of the original dataset, respectively. Specifically, the training set encompasses 14,204 images (about 69.88%), the validation set includes 4,094 images (about 20.14%), and the test set contains 2,029 images (about 9.98%) as shown in Figure 2. It is important to note that each split is generated randomly and therefore cannot be reproduced.

Challenges encountered include class imbalance, where certain types of fractures were underrepresented. This was addressed using oversampling and data augmentation. Additionally, variability in image quality due to different X-ray machines was mitigated through contrast adjustment and normalization techniques.

It was conducted an error analysis to understand common misclassifications and suggest ways to mitigate these errors as shown in figure 3.

EXPERIMENTATION

We employ the YOLOv8 model during the model's training procedure. We established 200 as the overall number of epochs. While our current model parameters were chosen based on initial performance benchmarks and computational constraints, further tuning and the inclusion of more sophisticated features could enhance accuracy. Future work will explore hyperparameter optimization and the integration of additional data attributes to validate this hypothesis. Preliminary tests with different parameter sets have shown promise, indicating a possible increase in accuracy, though these are still in the exploratory phase**.**

- **Accuracy:** Accuracy = (TP + TN) / (TP + TN + FP + FN)
- **Precision:** Precision = TP / (TP + FP)
- **Recall:** Recall = TP / (TP + FN)
- **F1-Score:** F1 = 2×Precision×Recall / Precision + Recall

These formulae will be accompanied by explanations of their relevance to the evaluation of the model's performance.

Intersection over Union (IoU)

The intersection over Union (IoU), a commonly used metric in object identification, measures the degree of overlap between the projected bounding box and the ground truth. The higher the IoU, the more accurate the prognosis [31].

The Precision-Recall Curve (P-R Curve)

Plotting on the x-axis recall versus on the y-axis precision, each point on the P-R Curve represents a distinct threshold value. Recall is the responsiveness of the method, demonstrating its capacity to identify all pertinent examples; In contrast, precision represents the proportion of accurate positive forecasts.

F1-score

This measure, which provides a balanced estimation of the model accuracy, is described as combining recall and precision, Precision and Confidence, Recall and Confidence, F1 score Confidence Curve into one figure 4, 5, 6 and 7 simultaneously.. Because it takes into consideration the two types of error and incorrect results in its

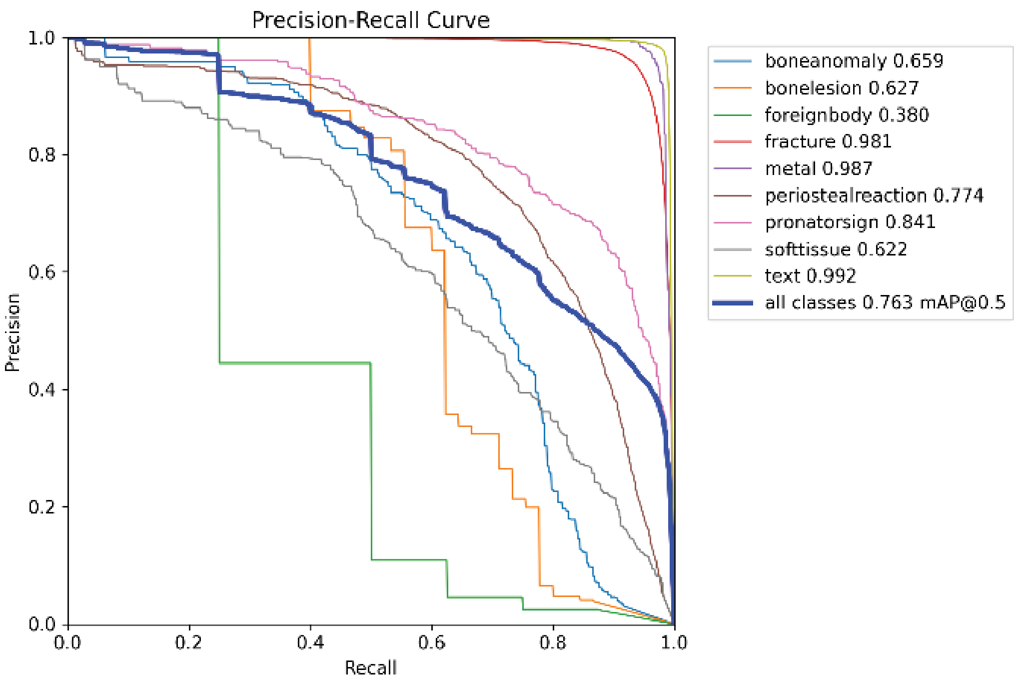

Figure 4. Precision-recall curve.

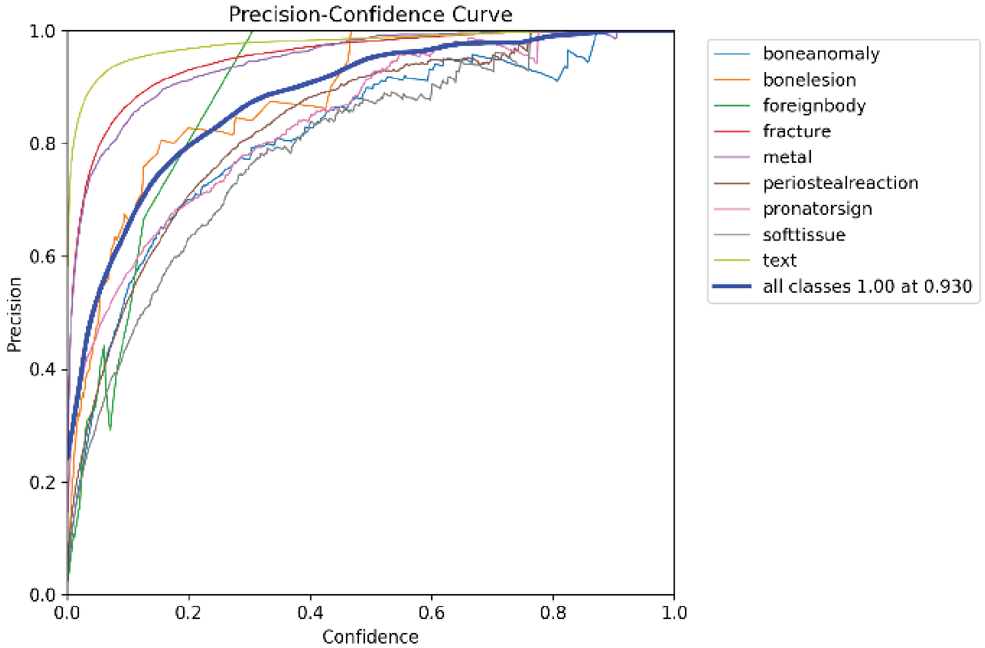

Figure 5. Precision-confidence curve.

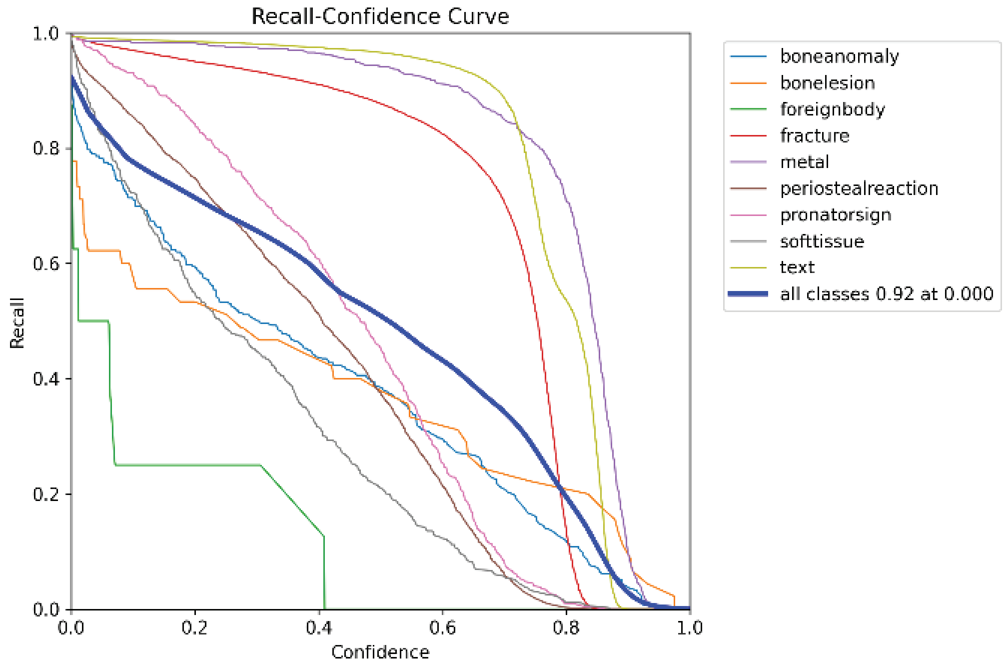

Figure 6. Recall-confidence curve.

computation, the F1-score is especially helpful in situations when the category allocation is asymmetrical.

Web App

Upon finishing the training of the model, we make use of a Python framework called Streamlit, for the creation of a web application. Streamlit is an open-source framework for quickly creating visually appealing web applications for machine learning and data science. This Python library is designed specifically for machine learning engineers. Our model has been converted to the onnx format and integrated into the web application. The working of the web

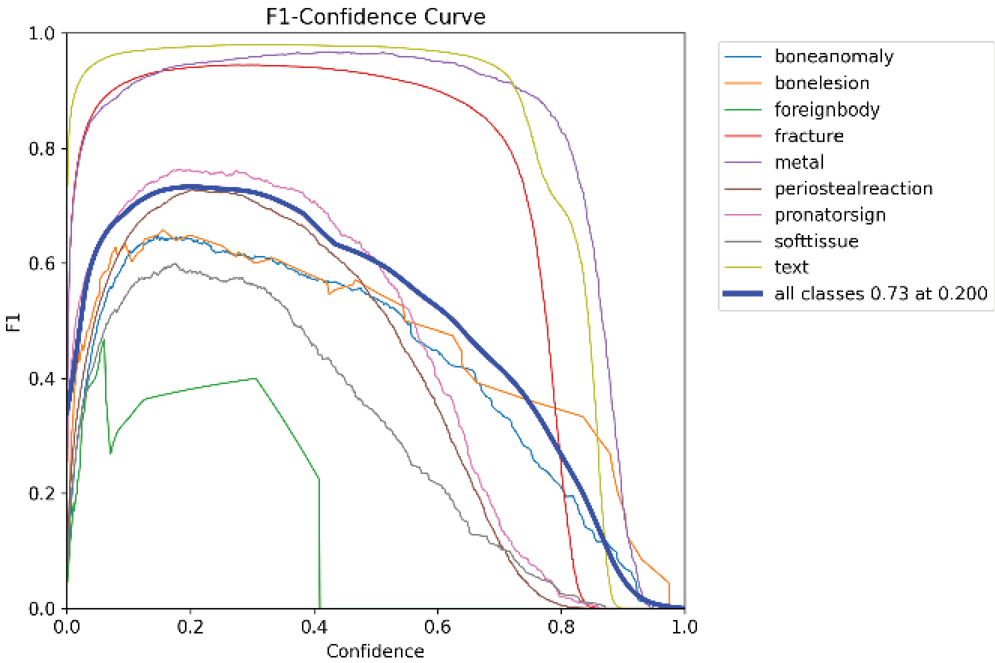

Figure 7. F1 score confidence curve.

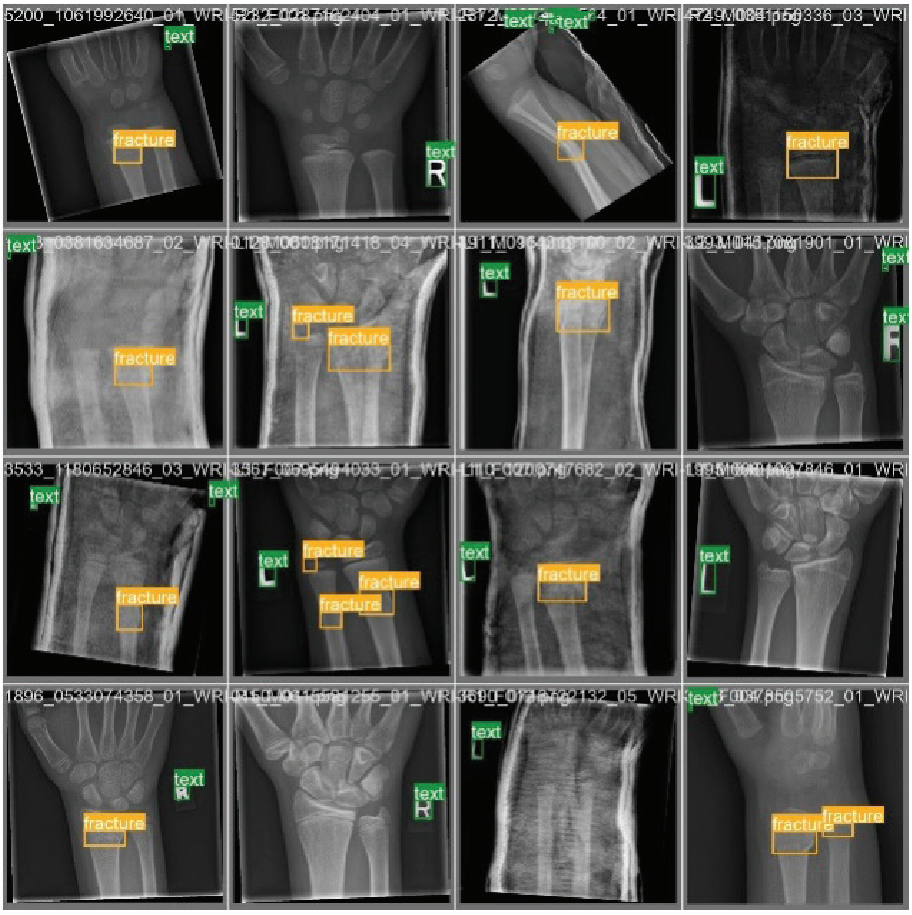

Figure 8. Demonstration of utilizing the web application for remotely detecting fractures.

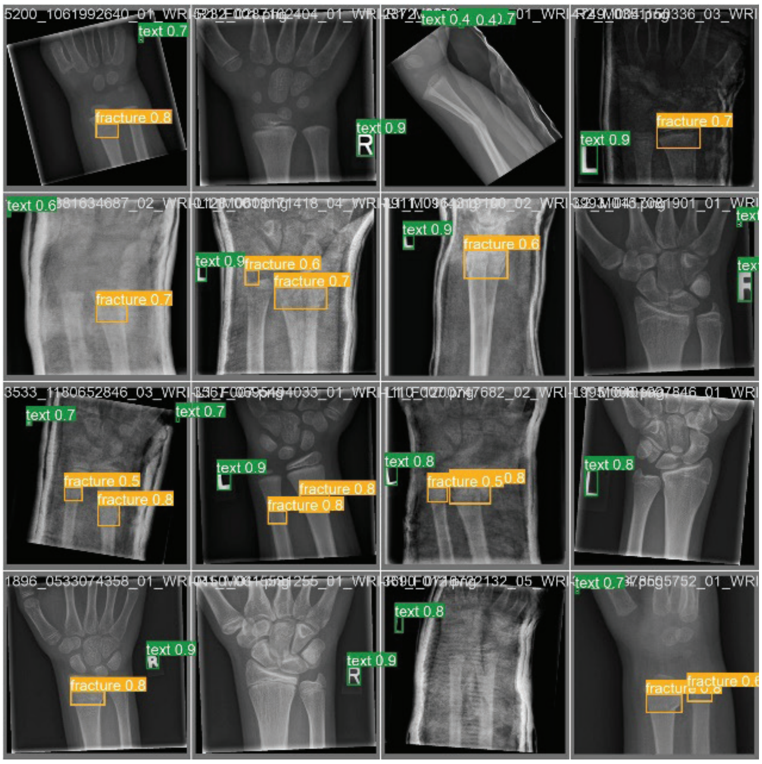

Figure 9. Illustrations of detecting fractures on X-ray images (images labeled manually).

Figure 10. Illustrations of detecting fractures on X-ray images (images predicted by the model).

application is illustrated in Figure 10. The application, titled "Bone Fracture Detection," allows users to upload images, make predictions by adjusting the threshold slider, and download the results. In essence, the application is intended to aid surgeons in analyzing fractures in x-ray images.

RESULTS AND DISCUSSION

We assessed the YOLOv8 model's capacity to identify fractures in x-ray pictures of human wrists in our investigation. We assessed the reliability of our YOLOv8 program against other advanced models based on the GRAZPEDWRI-DX dataset, and the model demonstrated exceptional performance. When compared to earlier models, our YOLOv8 model continuously showed better accuracy in diagnosing bone fractures. We assessed accuracy criteria including recall, precision, and F1-score to demonstrate the versatility and efficacy of our method across a range of fracture patterns.

Table 1 shows the comparison of our model with YOLOv5, YOLOv7, YOLOv7 using Convolution Block Attention Module (CBAM), along with YOLOv7 algorithm using Global Attention Mechanism (GAM) in terms of mAP, precision, recall, and F1 values. The outcomes unequivocally show that our model outperforms other models with the greatest values of performance metrics.

The creation of an application for mobile devices especially intended for the identification for fractures in x-ray pictures is the main objective of this work. We use a fracture

Table 1. Model compatibility result

Model	Precision	Recall	F1	mAP 50
YOLOv5	0.682	0.581	0.607	0.626
YOLOv7	0.556	0.582	0.569	0.628
YOLOv7 (CBAM)	0.709	0.593	0.646	0.633
YOLOv7 (GAM)	0.745	0.574	0.646	0.634
Ours	0.801	0.712	0.753	0.762

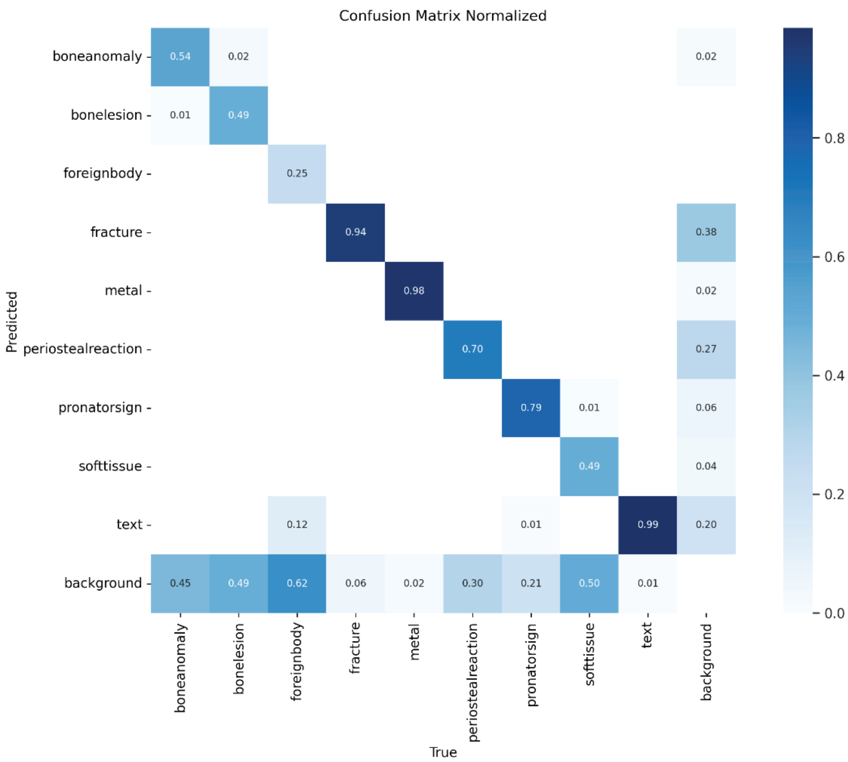

Figure 11. The confusion matrix for distribution of false positives and false negatives.

detection framework for our method. The results shown in Figure 8 and 9 shows a contrast between the outcomes our model anticipated and the ones that came from radiologists' manual annotation. The results unambiguously show that our approach performs better when it comes to detecting fractures in situations where there is just one fracture. It is crucial to remember that in situations when there are numerous, dense fractures, forecast accuracy are affected.

Our results indicate that the YOLOv8 model can significantly reduce diagnostic times in clinical settings, providing near-instantaneous fracture detection. However, limitations include the model's dependency on high-quality images and potential performance variability across different patient demographics. To address these limitations, future work will involve extensive testing in diverse clinical environments and the development of adaptive models that can handle varying image qualities. Our findings demonstrate that the YOLOv8 model not only outperforms previous models in terms of mAP but also offers practical improvements in speed and accuracy, which are critical in clinical settings. This enhanced performance can greatly aid in timely and accurate diagnosis of pediatric wrist fractures, especially in emergency departments where rapid decision-making is crucial.

We have also compared our results with existing literature. For example, the study by Rui-Yang Ju and Weiming Cai reported a mAP of 0.634 using an improved YOLOv7 model. Our YOLOv8 model's superior performance with a mAP of 0.762 underscores the advancements made in our approach. These results highlight the effectiveness of our model in detecting fractures, potentially reducing the rate of missed diagnoses. The confusion matrix for distribution of false positives and false negatives is shown in Figure 11.

In terms of clinical relevance, we discussed the practical applications of our model. The high accuracy and speed of the YOLOv8 model can significantly assist clinicians in diagnosing fractures accurately and quickly. This is particularly beneficial in smaller hospitals with limited radiological expertise. Moreover, integrating our model into mobile diagnostic tools can provide real-time assistance to surgeons and radiologists, thereby improving patient outcomes.

We have also addressed the limitations of our study more thoroughly. One limitation is the size of the GRAZPEDWRI-DX dataset. We acknowledge that larger and more diverse datasets are necessary for more robust validation. Additionally, while our model performs well in detecting fractures, it still faces challenges in distinguishing subtle fracture patterns, which we aim to address in future work.

Looking ahead, we propose several future research directions. We plan to expand our dataset to include more diverse patient populations and fracture types. We also aim to integrate additional imaging modalities, such as MRI and CT, to enhance the diagnostic capabilities of our model. Furthermore, exploring the application of our model in detecting fractures in other parts of the body and integrating it into comprehensive diagnostic tools will be valuable avenues for future research.

CONCLUSION

The suggested YOLOv8 and image processing-based bone fracture identification system can accurately detect fractures from X-ray pictures. Although the YOLOv8 model has not received much attention in the field of medical image interpretation, In order to enhance the model's performance, we have employed it for fracture detection and included methods for augmenting data. Furthermore, we have created a web application which is intended to analyze -ray pictures in order to locate fractures. Our application's main goal is to help surgeons correctly interpret these x-ray pictures, which will lower the possibility of a misdiagnosis and, in the end, provide a more thorough informational framework for surgical treatments. The program is being hosted locally for the time being, but we want to deploy it eventually. Once our program is implemented, It will make it possible for inexperienced surgeons in underdeveloped nations to study x-ray pictures on their mobile devices.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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