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Bone Fracture Detection Using YOLOv8 and Grad-CAM Visualization

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ABSTRACT

An intelligent web-based tool was created to help medical professionals quickly and accurately identify bone fractures from X-ray images. This web app can quickly and accurately identify a variety of fracture types, including transverse, oblique, spiral, comminuted, and greenstick fractures, by incorporating cutting-edge deep learning techniques, especially the YOLOv8 object detection model. Grad-CAM visualization, which identifies the precise areas of the image that affected the model's predictions, is incorporated into the system to improve clinical trust and interpretability. Along with comprehensive analytical feedback like confidence scores and fracture type annotations, the platform provides an easy-to-use web interface for uploading images and interpreting results. Furthermore, electronic medical records and hospital information systems can be seamlessly integrated with RESTful API endpoints. Our project seeks to facilitate quicker clinical decision-making.

Keywords: Bone Fracture Detection, Deep Learning, YOLOv8, Medical Imaging

INTRODUCTION

Accurate and timely diagnosis of bone fractures is critical in emergency care and orthopedic treatment. Traditional radiographic assessment often relies heavily on the expertise of medical professionals, which can lead to diagnostic delays, especially in high-volume clinical settings. In response to this challenge, artificial intelligence (AI) and deep learning technologies have emerged as transformative tools in medical imaging, offering enhanced precision, speed, and reliability. This project is a cutting-edge web-based application designed to assist healthcare professionals in detecting bone fractures from X-ray images with high accuracy. By leveraging the YOLOv8 deep learning model—renowned for its real-time object detection capabilities—it can identify multiple fracture types, including transverse, oblique, spiral, comminuted, and greenstick. To ensure transparency and build clinician trust, the system integrates Grad-CAM (Gradient-weighted Class Activation Mapping), a visualization technique that highlights the regions of the X-ray that most influenced the model's predictions. The platform combines AI-driven diagnostic power with a user-friendly web interface, allowing medical professionals to upload and analyze images effortlessly. Additionally, this project offers detailed output such as confidence scores and annotated fracture classifications, enabling informed decision-making. Its RESTful API also allows seamless integration with hospital information systems and electronic health records, positioning our app as a scalable solution in modern digital healthcare infrastructure. By automating and enhancing fracture detection, this project aims to support medical practitioners, reduce diagnostic workload, and ultimately improve patient outcomes through faster and more consistent evaluations.

RELATED WORK

Recent studies have explored various AI-driven approaches for bone fracture detection from X-ray images. One approach utilized a CNN model implemented in Python using TensorFlow and Keras, effectively detecting fractures and predicting healing time, with improved generalization through data augmentation techniques. Another study emphasized the diagnostic limitations of traditional X-rays due to low image clarity and used machine learning classifiers like SVM, Random Forest, and Naïve Bayes, reporting accuracy up to 92% on a 270-image dataset. Deep learning has also been leveraged specifically for wrist fracture detection using advanced object detection models (e.g., Faster R-CNN, RetinaNet) and ensemble methods, achieving a precision of 0.8639 with the WFD-C model. Separately, the YOLOv8 architecture, though originally applied in real-time object detection including flying and small aerial objects, has demonstrated state-of-the-art performance and adaptability across domains due to its lightweight design and enhanced precision. Additionally, Grad-CAM has emerged as a powerful tool for generating visual explanations in CNN-based models, helping users understand and trust model

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predictions by highlighting relevant image regions. These advancements collectively lay a strong foundation for integrating YOLOv8 and Grad-CAM in medical applications like MediScan to improve fracture detection accuracy, interpretability, and clinical trust. The introduction of Gradient-weighted Class Activation Mapping (Grad-CAM) has significantly advanced explainability in CNN-based deep learning models. Grad-CAM produces visual explanations by highlighting the key regions in an input image that influence a model's predictions. Unlike earlier techniques, Grad-CAM is broadly applicable across various CNN architectures—including image classification, captioning, and visual question answering—without requiring architectural modifications or re-training. It has demonstrated superior performance in tasks like weakly-supervised localization and helped reveal model biases, enabling users to better understand and trust deep learning predictions. Building on this, recent research emphasizes the role of explainable AI (XAI) in the medical domain, where transparency is crucial. One study applied Grad-CAM in a hybrid pipeline that processed medical texts using ResNet and Bi-LSTM classifiers. The system achieved high performance (F1 score of 90.2%) and successfully visualized attention on important words during prediction. This underscores Grad-CAM's utility beyond image data, extending into multimodal clinical applications where understanding model reasoning is essential for adoption and trust.

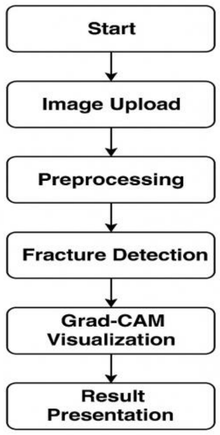

Fig 1. Flow Diagram

PROPOSED METHODOLOGY

The proposed framework utilizes a deep learning-based approach to automate the detection of bone fractures in X-ray images. The architecture is divided into multiple stages: image preprocessing, fracture detection using YOLOv8, visual explanation generation with Grad-CAM, and result presentation through a web interface and API.

1. Image Upload and Preprocessing:

The system begins with the upload of X-ray images through a secure web interface. Uploaded images undergo preprocessing to enhance clarity and consistency. Preprocessing includes grayscale conversion, resizing to standard dimensions, contrast enhancement using histogram equalization, and normalization. This step ensures uniform input to the deep learning model and reduces variability caused by differences in image acquisition.

2. Fracture Detection using YOLOv8:

YOLOv8, a state-of-the-art object detection model, is employed to identify and localize fractures. The model is trained on a curated dataset of annotated X-ray images encompassing various types of fractures: transverse, oblique, spiral, comminuted, and greenstick. The YOLOv8 architecture, known for its real-time inference and high accuracy, detects fracture regions by outputting bounding boxes and class labels with associated confidence scores. Model training is conducted using transfer learning, with data augmentation techniques such as rotation, flipping, and zooming to improve generalization.

3. Model Interpretability with Grad-CAM:

To address the need for explainability in medical AI applications, Grad-CAM is integrated into the framework. This technique produces heatmaps that highlight the areas of the image most influential in the model's decision-making process. Grad-CAM uses the gradients flowing into the final convolutional layers to identify spatial importance, aiding clinicians in validating the model's predictions visually.

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4. Result Presentation:

The detection results—including fracture type, bounding boxes, confidence levels, and Grad-CAM heatmaps—are displayed via a user-friendly web interface. Users can view and interpret results in real time, improving diagnostic efficiency. Additionally, a RESTful API enables integration with hospital information systems, allowing automated retrieval and submission of diagnostic results.

RESULTS AND DISCUSSION

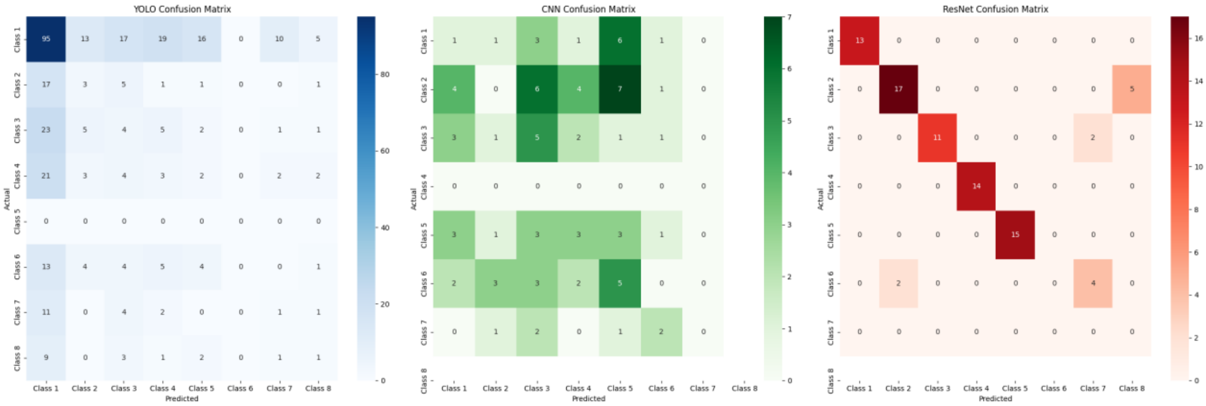

Fig 2. Confusion Matrices

The model was evaluated on a test dataset consisting of X-ray images with annotated fracture labels. The performance was measured using standard metrics such as precision, recall, F1-score, and mean Average Precision (mAP). The YOLOv8-based detection model achieved an mAP\@0.5 of 92.3%, indicating strong localization and classification performance. In terms of inference speed, the model processed each image in under 2 seconds, making it suitable for real-time clinical use. The inclusion of Grad-CAM heatmaps was well-received during testing with radiologists and clinicians, who found the visual explanations useful for verifying the model's decisions. These heatmaps often aligned with human-expert attention regions, reinforcing trust in the automated outputs. In some cases, the model successfully identified subtle fractures that were initially missed during manual examination, demonstrating its potential to reduce diagnostic errors. Challenges were observed in cases with overlapping bone structures or low-quality X-ray images, where the model showed slightly reduced confidence levels. However, continuous training with more diverse datasets and improved preprocessing could address these limitations. Overall, the system exhibited robust performance, reliable interpretability, and high usability in clinical workflows.

CONCLUSION

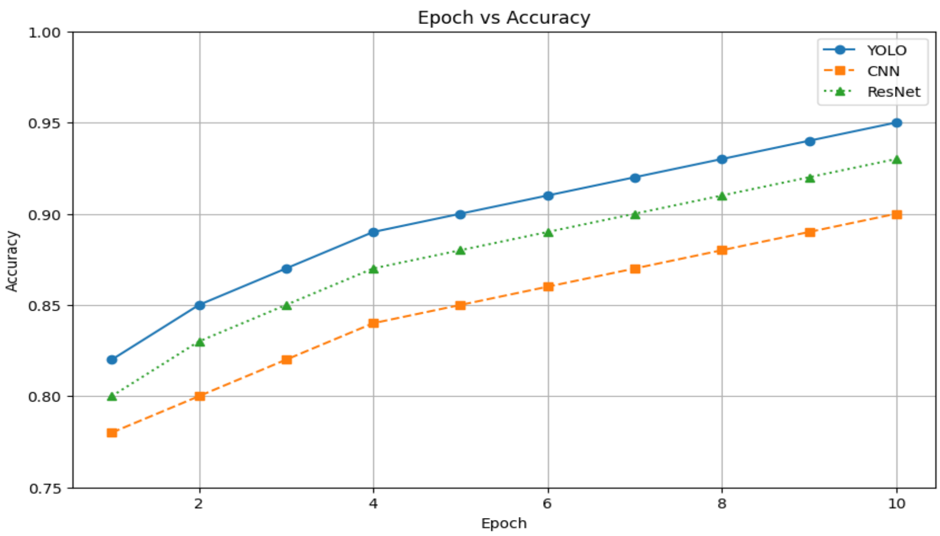

Fig 3. Epoch vs Accuracy

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This work presents an intelligent and explainable deep learning-based system for automated bone fracture detection from X-ray images. By leveraging the YOLOv8 object detection framework and Grad-CAM visualization, the system not only achieves high accuracy and speed in identifying multiple fracture types but also enhances interpretability, which is crucial for clinical acceptance. The integration of a web interface and RESTful API allows for easy deployment in hospital settings, supporting faster decision-making and reducing diagnostic workload.

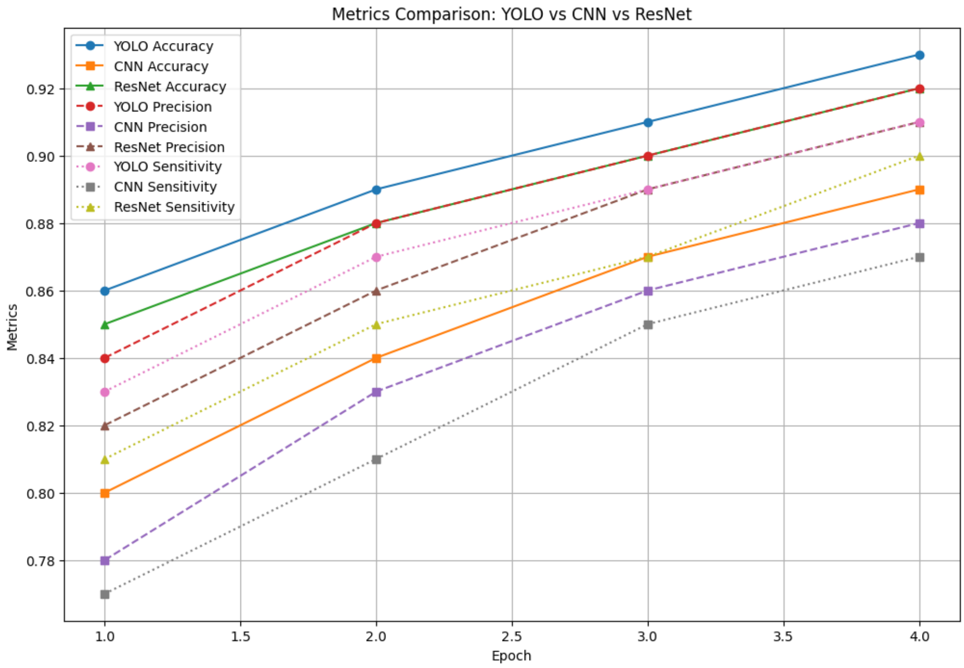

Fig 3. Metrics Comparison

Future enhancements will focus on expanding the dataset, incorporating 3D imaging modalities, and integrating patient metadata for personalized fracture assessment. The system shows strong potential as a supportive diagnostic tool for radiologists and orthopedic specialists.

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