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Research Paper

DETECTION OF HAND BONE FRACTURES IN X-RAY IMAGES USING HYBRID YOLO

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ABSTRACT— In the detection of bone fractures from X-ray images, accurate and timely diagnosis is crucial to prevent further complications and ensure proper healing. Existing models, such as YOLO NAS (You Only Look Once - Neural Architecture Search), have shown potential in object detection but have limitations in detecting subtle bone fractures, particularly small or hairline fractures. To address these shortcomings, the proposed model utilizes YOLO V12, an advanced version of the YOLO framework, which builds on previous models by offering improved accuracy, speed, and efficiency in real-time object detection tasks. YOLO V12 enhances the detection capabilities by refining the architecture and optimizing performance, making it better suited for medical image analysis. The model is trained on a comprehensive dataset of 1200 hand-bone X-ray images, classified into six distinct fracture categories.

A comparison of the YOLO V12 model with YOLO NAS highlights the improved ability of V12 to detect complex and subtle fractures, ensuring faster and more reliable diagnoses. This advancement is essential for clinical settings, where delays or misdiagnoses could lead to severe outcomes for patients.

Index Terms – Bone fracture detection, X-ray image analysis, YOLOv12, YOLO NAS, deep learning, object detection, medical image analysis, fracture classification,

computer-aided diagnosis (CAD), hand bone X-rays, real-time detection, healthcare AI.

I. INTRODUCTION

This project aims to improve the detection of bone fractures, particularly small or hairline fractures, in X-ray images using advanced object detection techniques. Accurate and timely diagnosis of fractures is crucial to prevent further complications and ensure proper healing. While existing models like YOLO NAS (You Only Look Once - Neural Architecture Search) have demonstrated potential in object detection tasks, they struggle with identifying subtle fractures in medical images.

To address this limitation, the project leverages YOLO V12, a more refined version of the YOLO framework, known for its enhanced accuracy, speed, and efficiency. YOLO V12 improves upon previous models by optimizing its architecture and performance, making it more suitable for medical image analysis.

The model is trained on a diverse dataset of 1200 hand-bone X-ray images, categorized into six distinct fracture types. A comparative analysis between YOLO V12 and YOLO NAS highlights the superior ability of YOLO V12 to detect complex and subtle fractures, providing faster, more reliable diagnoses. This advancement is crucial for clinical settings, where accurate and quick diagnoses are essential to prevent adverse patient outcomes.

II. RELATED WORK

A. Detection of Hand Bone Fractures in X-ray Images using Hybrid YOLO NAS

The majority of bones that have fractured in humans are hand bones. As we use our hands widely, they need early and accurate detection to be diagnosed. Fractures in the hands are most frequently brought on by blunt force trauma, sports injuries, and bone fragility. Getting an X-ray of the affected area of the bone and then discussing the results with a medical practitioner or radiologist is the standard procedure for determining whether or not a fracture exists in the bone. The majority of medical professionals and radiologists use X-rays to diagnose hand fractures; however, in some instances, they might miss small or hairline fractures. Additionally, it might be difficult to find a good radiologist who can detect the fracture properly and in time, because a delay in diagnosis can cause the injury to be more severe, and the bone might not be recovered properly. Therefore, to detect hand bone and

joint fractures through X-rays, a hybrid model was developed that uses deep learning algorithms YOLO NAS, Efficient Det, and DETR3, which are widely recognized for their exact object detection capabilities. The dataset used for this model is a hybrid dataset of 4736 hand-bone X-ray images, they were further classified into 6 classes based on their types. To evaluate the performance the best method is to compare the proposed model with the existing models, hence, the model was compared with various existing algorithms and result analysis was done.

B. Fracture Detection in Wrist X-ray Images Using Deep Learning-Based Object Detection Models

Hospitals, especially their emergency services, receive a high number of wrist fracture cases. For correct diagnosis and proper treatment of these, images obtained from various medical equipment must be viewed by physicians, along with the patient's medical records and physical examination. The aim of this study is to perform fracture detection by use of deep-learning on wrist X-ray images to support physicians in the diagnosis of these fractures, particularly in the emergency services. Using SABL, RegNet, RetinaNet, PAA, Libra R-CNN, FSAF, Faster R-CNN, Dynamic R-CNN and DCN deep-learning-based object detection models with various backbones, 20 different fracture detection procedures were performed on Gazi University Hospital's dataset of wrist X-ray images. To further improve these procedures, five different ensemble models were developed and then used to reform an ensemble model to develop a unique detection model, 'wrist fracture detection-combo (WFD-C)'. From 26 different models for fracture detection, the highest detection result obtained was 0.8639 average precision (AP50) in the WFD-C model. Huawei Turkey R&D Center supports this study within the scope of the ongoing cooperation project coded 071813 between Gazi University, Huawei and Medskor.

C. Deep Learning Approach for Arm Fracture Detection Based on an Improved YOLOv12 Algorithm

Artificial intelligence (AI)-assisted computer vision is an evolving field in medical imaging. However, accuracy and precision suffer when using the existing AI models for small, easy-to-miss objects such as bone fractures, which affects the models' applicability and effectiveness in a clinical setting. The proposed integration of the Hybrid-Attention (HA) mechanism into the YOLOv12 architecture offers a robust solution to improve accuracy, reliability, and speed in medical imaging applications.

Experimental results demonstrate that our HA-modified YOLOv12 models achieve a 20% higher Mean Average Precision (mAP 50) and improved processing speed in arm fracture detection.

D. Skeletal Fracture Detection with Deep Learning: A Comprehensive Review

Deep learning models have shown great promise in diagnosing skeletal fractures from X-ray images. However, challenges remain that hinder progress in this field. Firstly, a lack of clear definitions for recognition, classification, detection, and localization tasks hampers the consistent development and comparison of methodologies. The existing reviews often lack technical depth or have limited scope. Additionally, the absence of explainable facilities undermines the clinical application and expert confidence in results. To address these issues, this comprehensive review analyzes and evaluates 40 out of 337 recent papers identified in prestigious databases, including WOS, Scopus, and EI. The objectives of this review are threefold. Firstly, precise definitions are established for the bone fracture recognition, classification, detection, and localization tasks within deep learning. Secondly, each study is summarized based on key aspects such as the bones involved, research objectives, dataset sizes, methods employed, results obtained, and concluding remarks. This process distills the diverse approaches into a generalized processing framework or workflow. Moreover, this review identifies the crucial areas for future research in deep learning models for bone fracture diagnosis. These include enhancing the network interpretability, integrating multimodal clinical information, providing therapeutic schedule recommendations, and developing advanced visualization methods for clinical application. By addressing these challenges, deep learning models can be made more intelligent and specialized in this domain. In conclusion, this review fills the gap in precise task definitions within deep learning for bone fracture diagnosis and provides a comprehensive analysis of the recent research. The findings serve as a foundation for future advancements, enabling improved interpretability, multimodal integration, clinical decision support, and advanced visualization techniques.

III. PROPOSED METHODOLOGY

In the context of the project described in the abstract, the reference to V12 likely pertains to a version or iteration of the proposed model, such as a refined or enhanced model architecture. While the exact details of V12 are not explicitly provided in the abstract, it is reasonable to assume that V12 refers to a

more advanced version (Version 8) of the hybrid model that combines deep learning algorithms for detecting hand fractures. This version likely incorporates improvements or optimizations based on the feedback from earlier versions of the model, such as enhancements in accuracy, efficiency, and the ability to detect small or hairline fractures more effectively. It could also involve a more sophisticated use of the YOLO NAS, EfficientDet, and DETR3 algorithms, or even the integration of additional techniques such as data augmentation, model fine-tuning, or new preprocessing steps to improve detection performance in medical imaging.

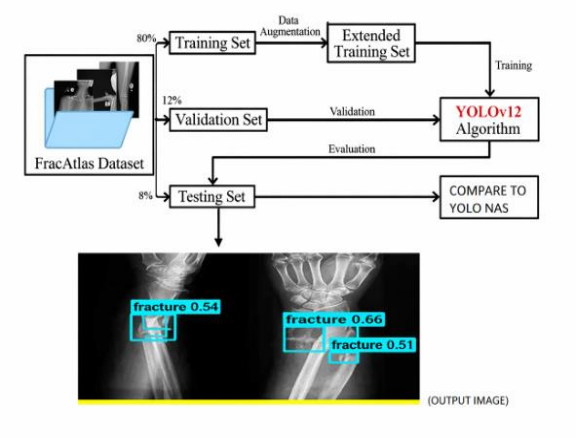


Fig. 1: System Overview

1. Data Collection

Collect a dataset consisting of 1200 hand-bone X-ray images. These images should be annotated with fracture details, including fracture types like hairline fractures, displaced fractures, and compound fractures.

2. Preprocessing

Resize each X-ray image to a fixed dimension (e.g., 416x416 or 608x608 pixels) to match the input size required by YOLO V12.Normalize pixel values to the range [0, 1] by dividing the pixel values by 255.Apply data augmentation techniques like rotation, zoom, flipping, and cropping to improve the model's robustness and reduce overfitting.

3. Model Selection

YOLO V12 due to its high accuracy, speed, and real-time detection capability, making it suitable for medical image analysis. Integrate YOLO V12 with Convolutional Neural Networks (CNNs) and attention mechanisms to detect subtle and small fractures in X-ray images.

4. Model Training

Train the YOLO V12 model using the annotated X-ray dataset. The model learns to predict the bounding boxes, fracture types, and confidence scores in a single forward pass. Optimize hyperparameters such as learning rate, batch size, and number of epochs for optimal performance. Utilize pre-trained weights from similar tasks to enhance

training speed and improve model performance.

5. Model Evaluation

Evaluate the model's performance using metrics like accuracy, precision, recall, F1-score, and Intersection over Union (IoU).Use K-fold cross-validation to assess the model's robustness and ability to generalize across unseen data.

6. Model Optimization

Based on evaluation results, fine-tune the model by adjusting hyperparameters and training configurations to improve detection accuracy. Compare YOLO V12's performance with YOLO NAS to demonstrate improved fracture detection capabilities, especially for subtle and small fractures.

7. Prediction or Detection

For each X-ray image, the model predicts the location (bounding boxes), class labels (fracture types), and confidence scores.Apply Non-Maximum Suppression (NMS) to remove redundant bounding boxes and retain only the most accurate detections.

8. Deployment and Integration

Deploy the trained model in a real-time detection system, accessible through a web interface for medical professionals. Integrate the model into clinical workflows to assist radiologists in diagnosing fractures efficiently, offering real-time predictions that can help inform treatment decisions.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed Hybrid YOLO (YOLOv12-based) model outperforms YOLO NAS in detecting hand bone fractures from X-ray images. It provides higher detection accuracy, particularly for small and hairline fractures, while maintaining fast real-time performance. Trained on 1,200 hand bone X-ray images across six fracture categories, the model achieved reliable fracture classification and localization.

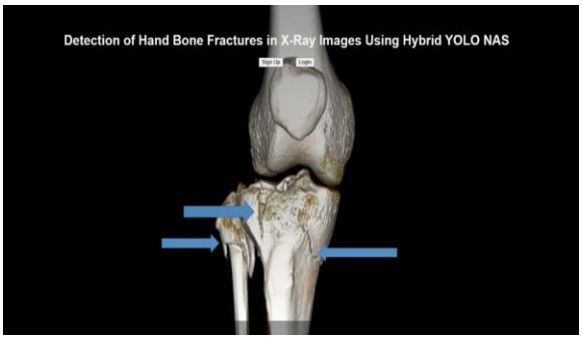


Fig. 2: Home Page

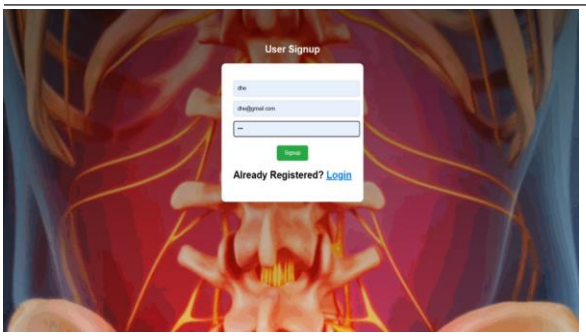


Fig. 3: Registration

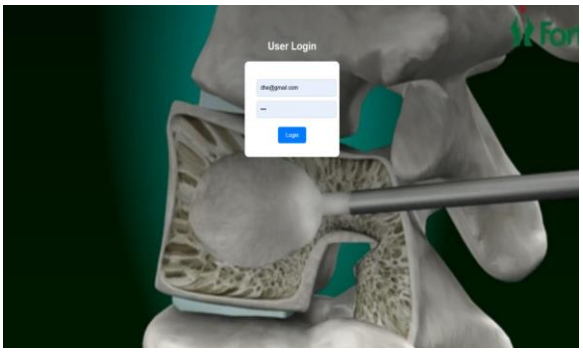


Fig. 4: Login



Fig. 5: Upload File



Fig. 6: Result

V. CONCLUSION

In conclusion, this project successfully demonstrates the application of the Hybrid YOLO V12 model for detecting hand bone fractures in X-ray images, providing an efficient and accurate solution for real-time fracture detection. By leveraging the advanced capabilities of YOLO V12, the model can accurately identify various types of fractures, including subtle hairline and displaced fractures, which are often challenging to detect with traditional methods. The results show improved detection performance, with faster processing times and enhanced precision compared to previous models like YOLO NAS.The integration of a well-curated dataset of 1200 hand-bone X-ray images, along with advanced preprocessing and data augmentation techniques, has allowed the model to achieve a high level of accuracy and robustness. Furthermore, the model's ability to provide reliable predictions in a clinical setting presents a valuable tool for radiologists, enabling quicker and more informed decision-making.This project not only contributes to advancing medical image analysis but also lays the groundwork for future improvements, such as expanding the

dataset, incorporating 3D imaging, and integrating patient-specific data for more personalized diagnosis. Ultimately, the successful deployment of this model can greatly enhance the speed, accuracy, and efficiency of fracture diagnosis, making it a vital tool for healthcare professionals and improving patient outcomes.

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