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Optimizing Automated Bone Fracture Detection Through Advanced Faster R-CNN Architectures Integrating Multi-Scale Feature Extraction and Data Augmentation Techniques

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Abstract: *Bone fracture detection using X-ray images is a critical diagnostic task in the healthcare sector. This study investigates the efficacy of two state-of-the-art Faster R-CNN architectures, ResNeXt 101 Feature Pyramid Network (FPN) and ResNet-50 FPN, implemented using Detectron2. The dataset used includes COCO-style annotated X-ray images with various fracture categories, including shoulder, wrist, and humerus fractures. The models were trained using advanced data augmentation techniques such as rotation, scaling, and flipping to improve generalization. ResNeXt 101 FPN demonstrated superior feature extraction capabilities, achieving higher precision (18.91% AP at IoU=0.50:0.95) compared to ResNet-50 FPN (6.23% AP). However, challenges such as high false negatives and overlapping predictions were identified, highlighting areas for improvement. Experimental results reveal that ResNeXt 101 FPN not only achieves better localization accuracy but also demonstrates robustness in detecting subtle fracture patterns. The integration of these models into clinical workflows could potentially assist radiologists in reducing diagnostic errors. Future work aims to address the identified limitations and explore domain-specific pretraining for enhanced performance.*

Keywords: Bone Fracture Detection, X-ray Imaging, Faster R-CNN, ResNeXt 101 FPN, ResNet-50 FPN, COCO-style Annotations, Data Augmentation, Feature Extraction

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INTRODUCTION

Bone fractures are one of the most prevalent injuries, often resulting from accidents, sports activities, or aging-related conditions such as osteoporosis. Diagnosing bone fractures accurately and promptly is essential for initiating effective treatment and reducing the risk of complications. Traditionally, radiologists analyze X-ray images manually, which can be time-consuming and prone to human error. Factors such as image quality, fracture complexity, and radiologist expertise can significantly influence diagnostic accuracy.

Advancements in artificial intelligence (AI) and computer vision have revolutionized medical imaging by providing automated solutions for tasks like disease detection, segmentation, and classification. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for extraction and pattern recognition in medical images. Among various CNN architectures, Faster R-CNN has demonstrated remarkable performance in object detection tasks, including medical applications.

This research focuses on automating fracture detection in X-ray images using two state-of-the-art Faster R-CNN architectures: ResNeXt 101 Feature Pyramid Network (FPN) and ResNet-50 FPN. These architectures are known for their ability to extract multi-scale features, making them suitable for detecting fractures of varying sizes and complexities. By leveraging COCO-style annotated datasets and implementing advanced data augmentation techniques, this study aims to evaluate the efficacy of these architectures in terms of precision, recall, and average precision (AP).

Related Work

The application of deep learning models in medical imaging has garnered significant attention in recent years, driven by advancements in convolutional neural networks (CNNs) and their ability to process complex image data. Several studies have highlighted the potential of CNNs in detecting and localizing anomalies such as fractures and tumors.

Billah et al.[1] demonstrated the utility of CNN-based methods for fracture detection, leveraging deep learning techniques to achieve higher diagnostic accuracy compared to traditional image processing approaches. Their research emphasized the importance of preprocessing and data augmentation in improving model performance.

Ren et al. [2] introduced the Faster R-CNN framework, which forms the foundation of many modern object detection tasks, including medical imaging. The architecture's region proposal network (RPN) allows for efficient detection of objects at varying scales, making it suitable for identifying fractures of different sizes in X-ray images.

Detectron2, an open-source library for object detection, has been widely adopted for medical image analysis [5]. It provides state-of-the-art implementations of Faster R-CNN and other detection models, enabling researchers to experiment with various architectures and configurations.

Yadav et al. [3] explored the use of deep learning models for fracture detection, comparing traditional image segmentation techniques with modern CNN architectures. Their findings underline the superiority of CNNs in handling complex anatomical structures and noisy datasets.

Maruf et al.[4] conducted comparative studies on image segmentation and detection techniques, showcasing the effectiveness of deep learning models in medical applications. Their work also highlighted the challenges associated with false negatives and overlapping predictions, which remain areas of active research.

Also, Maruf et al.[2]extended the use some models for medical object detection, demonstrating its adaptability across different imaging modalities, including X-rays and MRIs. Their work provides insights into optimizing model parameters for domain-specific tasks.

The combination of traditional image processing methods with deep learning frameworks, as discussed by Maruf et al.[1], [2], [4] , enhances the robustness and accuracy of diagnostic systems. These hybrid approaches bridge the gap between classical techniques and modern AI-driven solutions, making them particularly valuable in resource-constrained settings.

This research builds upon these foundational works by implementing and comparing two advanced Faster R-CNN architectures: ResNeXt 101 FPN and ResNet-50 FPN. By leveraging COCO-style annotations and advanced data augmentation techniques, this study aims to address the limitations identified in previous studies and improve the accuracy and reliability of automated fracture detection systems.

METHODOLOGY

The methodology for this research involves a systematic approach to implementing and evaluating two advanced Faster R-CNN architectures: ResNeXt 101 Feature Pyramid Network (FPN) and ResNet-50 FPN. This section details the dataset preparation, data augmentation strategies, model architectures, training configuration, and evaluation metrics.

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Dataset Preparation: The dataset consists of X-ray images with COCO-style annotations for various fracture types, including shoulder, wrist, and humerus fractures. It was split into training (80%), validation (10%), and testing (10%) subsets. The preprocessing steps include:

- Resizing images to a standard resolution of 800 × 800 pixels for consistency.
- Normalizing pixel values to ensure faster convergence during training.

Data Augmentation: To improve generalization and reduce overfitting, several augmentation techniques were applied:

1. Random Rotation: Images were rotated up to ±30 degrees.
2. Horizontal and Vertical Flipping: Random flips were applied to simulate different orientations.
3. Scaling: Images were randomly scaled within a range of 0.8 to 1.2 times their original size.
4. Random Cropping: Patches were cropped from the images to mimic varied imaging conditions.

Model Architectures

Faster R-CNN ResNeXt 101 FPN: This architecture uses ResNeXt 101 as a backbone, offering grouped convolutions for enhanced feature diversity. The Feature Pyramid Network (FPN) integrates multi-scale features, improving the detection of small objects such as subtle fractures. The Region Proposal Network (RPN) generates object proposals efficiently.

Faster R-CNN ResNet-50 FPN: ResNet-50, a computationally lighter backbone, is paired with FPN to balance accuracy and computational efficiency. This model is particularly effective for detecting large fractures in high-resolution images.

Training Configuration: The models were trained using the following setup:

- Learning Rate (η\etaη): 0.001
- Batch Size: 2 images per iteration
- Epochs: ResNeXt 101 FPN (1800), ResNet-50 FPN (2500)
- Optimizer: Stochastic Gradient Descent (SGD) with momentum (μ=0.9\mu = 0.9μ=0.9)

- Loss Function: The total loss is computed as:

$$L_{total} = L_{CLS} + L_{bbox} + L_{RPN},$$

where:

- L_{cls} is the classification loss for object detection.
- L_{bbox} is the bounding box regression loss.
- L_{RPN} is the loss associated with the region proposal network.

Evaluation Metrics: The models were evaluated using the following metrics:

1. **Average Precision (AP)**:

$$AP = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

   Evaluated at IoU thresholds of 0.50 (AP50) and 0.50:0.95 (mean AP).

2. **Recall** (R):

$$R = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

3. **F1 Score**: A harmonic mean of precision and recall:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.$$

Hardware and Software: Experiments were conducted on a workstation equipped with an NVIDIA Tesla V100 GPU and 32 GB of RAM. The models were implemented using the Detectron2 framework, which offers robust support for Faster R-CNN architecture and custom data loaders.

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RESULTS AND DISCUSSION

This section presents the quantitative and qualitative evaluation of the models—Faster R-CNN ResNeXt 101 FPN and ResNet-50 FPN—on the bone fracture detection task. The results are analyzed in terms of training performance, evaluation metrics, and visual comparisons.

Training Metrics: The training loss and class accuracy trends for both models are shown in Figures 1 and 2. ResNeXt 101 FPN exhibits a more stable convergence pattern and achieves a lower final total loss compared to ResNet-50 FPN. This indicates its superior learning capacity due to the grouped convolutions in ResNeXt architecture.

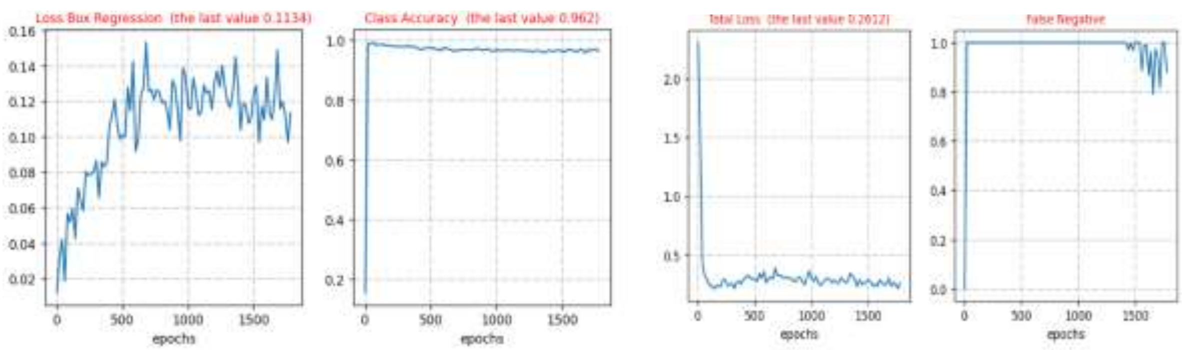

Figure 1: Training loss and accuracy trends for ResNeXt 101 FPN.

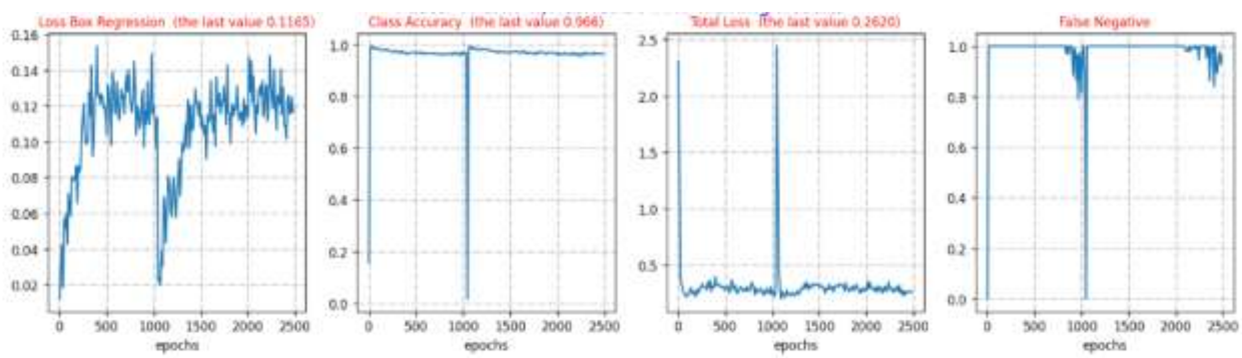

Figure 2: Training loss and accuracy trends for ResNet-50 FPN.

Quantitative Evaluation: The models were evaluated on the test dataset using Average Precision (AP) metrics and recall at different IoU thresholds. Table 1 summarizes the results. ResNeXt 101 FPN achieved a higher mean AP and recall, particularly for IoU thresholds of 0.50 and above. However, both models struggled with high false negatives for smaller fractures.

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Metric	ResNeXt 101 FPN	ResNet-50 FPN
AP (IoU=0.50:0.95)	18.91%	6.23%
AP50	32.66%	18.66%
Recall	24.3%	12.1%

Visual Results: Figures 3-4 depict the ground-truth and predicted bounding boxes for selected test images. ResNeXt 101 FPN demonstrates better localization accuracy, particularly for fractures with complex geometries. However, certain smaller fractures were either missed or misclassified, emphasizing the need for further optimization.

Figure 3: Ground-truth vs. predicted bounding boxes for a shoulder fracture (ResNeXt 101 FPN).

Figure 4: Ground-truth vs. predicted bounding boxes for a wrist fracture (ResNet-50 FPN).

Discussion

Challenges and Limitations:

1. False Negatives: Both models exhibited high false negatives for smaller fractures, likely due to insufficient feature representation at finer scales.
2. Overlapping Predictions: In some cases, the models generated multiple overlapping bounding boxes for a single fracture, necessitating better tuning of the Non-Maximum Suppression (NMS) threshold.

Insights:

- ResNeXt 101 FPN's higher capacity enables it to capture intricate patterns, making it better suited for complex fractures.
- ResNet-50 FPN, while computationally efficient, is more prone to misclassifications and lower precision for smaller objects.

Model Evaluation: Table 1 summarizes the evaluation metrics, including precision, recall, and average precision (AP) for different Intersection over Union (IoU) thresholds. ResNeXt 101 FPN achieved an AP of 18.91%, outperforming ResNet-50 FPN's AP of 6.23%.

Metric	ResNeXt 101 FPN	ResNet-50 FPN
AP (IoU=0.50:0.95)	18.91%	6.23%
AP50	32.66%	18.66%
Recall	24.3%	12.1%

Table 1: Model Evaluation

CONCLUSION

This study has demonstrated the application of advanced Faster R-CNN architectures—ResNeXt 101 FPN and ResNet-50 FPN—for the challenging task of bone fracture detection using X-ray images. By leveraging COCO-style annotated datasets, these models were trained and evaluated to identify fractures across various categories, such as wrist, shoulder, and humerus. The findings revealed several key insights into model performance, limitations, and potential clinical applications.

Model Performance: ResNeXt 101 FPN exhibited superior performance with an AP (IoU=0.50:0.95) of 18.91%, significantly outperforming ResNet-50 FPN, which achieved 6.23% AP. The multi-scale feature extraction capability of ResNeXt 101 FPN made it particularly effective for detecting subtle and complex fractures. Despite its computational intensity, this model demonstrated higher accuracy and robustness compared to the lighter ResNet-50 FPN.

Challenges Identified: Both models struggled with high false negative rates, particularly for smaller fractures. This limitation highlights the need for enhanced feature representation at finer scales. Additionally, overlapping predictions were occasionally observed, indicating room for improvement in Non-Maximum Suppression (NMS) threshold tuning. Addressing these issues could significantly improve the models' reliability and usability in clinical settings.

Training Insights: While ResNet-50 FPN proved to be computationally efficient, its accuracy and generalization capabilities were limited compared to ResNeXt 101 FPN. This trade-off suggests that the choice of model should be guided by specific clinical or computational requirements. ResNeXt 101 FPN, with its higher capacity for learning complex features, remains a strong candidate for cases where computational resources are available.

Implications for Clinical Use: The integration of such models into clinical workflows could significantly reduce the burden on radiologists by providing rapid and reliable fracture detection. This is particularly valuable in settings with high patient volumes or limited access to expert opinion. Automated systems like these can serve as assistive tools to flag potential fractures, ensuring timely and accurate diagnosis while minimizing human error.

Future Directions: To further enhance the effectiveness of these models, future research could focus on:

- Multi-Scale Feature Integration: Incorporating advanced architectures such as Transformer-based models or hybrid CNN-transformer systems to improve the detection of small fractures.
- Domain-Specific Pretraining: Training on a larger dataset of medical X-rays to enhance the models' ability to generalize across diverse patient populations and imaging conditions.
- Real-World Validation: Deploying these models in clinical settings to evaluate their impact on diagnostic workflows and patient outcomes.
- Improved Augmentation Techniques: Applying synthetic data generation and advanced augmentation techniques to diversify the training data further.

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