

Detecting Bone Fractures Utilizing Res-Net Variants

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Introduction and Project Overview

The intersection of medical imaging and artificial intelligence, particularly in diagnosing various medical conditions, represents a significant advance in healthcare. A critical aspect of this is the detection and classification of bone fractures, a vital component in orthopedic medicine. Traditionally, this process relies on the expertise of radiologists, but despite its effectiveness, it can be time-consuming and prone to human error. Addressing these limitations, our project utilizes deep learning, specifically Residual Networks (ResNet), for automated bone fracture detection from X-ray images.

We have utilized the comprehensive FracAtlas dataset, sourced from three medical centers, covering a broad spectrum of fracture types. This dataset forms the basis for testing and validating our models. Preprocessing included resizing and padding of images to suit ResNet's requirements, ensuring the removal of identifiable patient information to adhere to ethical standards. Our study employs various ResNet models, selected for their demonstrated efficacy in image recognition, particularly in the medical field. The training approach, tailored to address dataset imbalances, includes a 70-20-10 train-validation-test split and the use of focal cross-entropy loss. This methodology enhances the model's capacity to accurately classify different types of fractures.

The project's broader objective extends beyond developing a diagnostic tool; it aims to contribute to the fields of medical imaging and machine learning. By harnessing the potential of ResNet models for bone fracture detection, we aim to set a benchmark in research and potential clinical applications. The successful implementation of these models promises to significantly expedite diagnostic processes, reduce radiologists' workload, and potentially facilitate earlier treatments, thereby improving patient outcomes in orthopedic care.

Aims and Objectives

Primary Aim

Our research's primary aim is to develop and validate a deep learning-based model using Residual Networks (ResNet) for accurate, fast, and reliable detection and classification of bone fractures from X-ray images.

Specific Objectives

1. Data Collection and Preparation:

- Compile the FracAtlas dataset from various hospitals, ensuring diverse fracture representation.
- Meticulous preprocessing of images for machine learning model training.

2. Model Development and Optimization:

- Implement and fine-tune ResNet variants for fracture detection.
- Optimize models to handle imbalanced medical datasets using focal cross-entropy loss.

3. Performance Evaluation:

- Rigorously assess model performance in accuracy, sensitivity, specificity, and diagnostic efficacy.
- Compare effectiveness among ResNet variants.

4. Benchmarking Against Existing Practices:

- Benchmark models against traditional diagnostic methods.
- Identify areas for potential enhancement of radiological practices.

5. Exploration of Clinical Applications:

- Assess the feasibility of models in clinical settings.

- Collaborate with medical professionals for feedback and integration into clinical workflows.

Final Objective

The ultimate goal is to offer meaningful contributions to medical imaging and AI, laying a foundation for automated medical diagnostics innovations and improving patient care in orthopedics.

Literature Review

Overview

The integration of Deep Learning (DL) in medical image processing has revolutionized the field of diagnostic imaging, offering promising avenues for enhancing accuracy and efficiency in disease diagnosis. This literature review critically analyzes recent advancements in medical image classification, with a focus on the application of Res-Net architectures for bone fracture detection from X-ray images.

Medical Image Classification: A Survey

In the comprehensive survey by Litjens et al. (2017), titled "A survey of Medical Image Classification," published in [IEEE Xplore](#), the authors provide a detailed overview of various machine learning techniques employed in medical image analysis. The survey emphasizes the shift from traditional machine learning to more advanced deep learning methods, highlighting their superior performance in image classification tasks. This work is particularly relevant as it lays the foundational understanding of the evolution and current trends in medical image processing, setting the stage for the application of deep learning models like ResNet in our project.

Introduction to Deep Learning in Medical Image Processing

Another significant contribution is by Ker et al. (2018) in their work "Introduction to Deep Learning in Medical Image Processing," available at [ScienceDirect](#). This article explores the basic principles of deep learning and its application in medical image analysis. It discusses the challenges and potential of using DL in medical imaging, providing valuable insights into the

intricacies involved in implementing these models. This source is crucial for understanding the underlying mechanics of deep learning models and their relevance in enhancing diagnostic accuracy, particularly in bone fracture detection.

Deep Learning in Medical Images

Further expanding on the application of DL in medical imaging, the article "Deep Learning in Medical Images," published in [Wiley Online Library](#), offers an in-depth examination of various deep learning architectures, including Res-Net, for medical image classification. This paper is particularly pertinent to our project as it discusses the effectiveness of deep learning methods in distinguishing intricate patterns in medical images, a key aspect in fracture detection using X-ray scans.

These scholarly works collectively provide a comprehensive understanding of the current state and future potential of deep learning in medical image classification. They lay the groundwork for our research, underlining the significance of employing advanced DL models like Res-Net for effective and efficient bone fracture detection. The literature not only guides the methodological approach of our project but also underscores the broader impact of such technological advancements in medical diagnostics.

Methodologies

1. Dataset Information

The core of our research is based on the FracAtlas dataset, a meticulously curated collection of approximately 14,068 X-ray scans. These images were sourced from three distinct hospitals and diagnostic centers over the course of 2021 and 2022. The primary contributor was Lab-Aid Medical Center in Brahmanbaria, supplemented by Anupam General Hospital and Diagnostic Center in Bogra, and Prime Diagnostic Center in Barishal. The images, generated by Fujifilm and Philips devices, underwent a rigorous process of ethical clearance by the Institutional Research Ethics Board (IREB) in compliance with the Bangladesh Medical Research Council (BMRC) guidelines. This involved ensuring patient confidentiality through the removal of personally identifiable information and obtaining consent for data usage.



Figure 1. Photo of Fractured X-ray

2. Model Selection

Building upon the Residual Network (ResNet) architecture, our research implements several variants of ResNet, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. These models were chosen for their proven efficiency in image classification tasks and their unique abilities to handle deep network architectures without the associated pitfalls like vanishing gradients.

- **ResNet-18 and ResNet-34:** These are 'small' variants of the ResNet architecture, characterized by fewer layers. They are specifically designed for applications where computational efficiency is a priority, and the complexity of the data does not necessitate deeper networks. In our implementation, these models consist of sequential residual blocks, each with two layers. The ResNet-18 model comprises 2 blocks each in 4 layers, while ResNet-34 includes 3, 4, 6, and 3 blocks in each layer.
- **ResNet-50, ResNet-101, and ResNet-152:** Classified as 'large' ResNet variants, these models are more suited for complex datasets due to their increased depth. They feature three layers within each residual block. The ResNet-50 model is composed of 3, 4, 6, and 3 blocks, ResNet-101 has 3, 4, 23, and 3 blocks, and ResNet-152 features 3, 8, 36, and 3 blocks in each layer, respectively. These models are particularly beneficial for our project given the intricacies involved in classifying bone fractures from X-ray images.

In all these variants, the residual blocks are the core components. Each block in the 'small' ResNet models includes two convolutional layers, while in the 'large' models, there are three convolutional layers. These layers are responsible for feature extraction and are followed by batch normalization and ReLU activation. The residual connection, a hallmark of the ResNet

architecture, helps in mitigating the vanishing gradient problem by allowing shortcuts for gradients to flow through.

The decision to utilize a range of ResNet models provides a comprehensive perspective on the performance of different network depths and complexities. This approach allows us to determine the most effective model for our specific task of bone fracture detection from X-ray images, balancing between computational efficiency and diagnostic accuracy.

3. Preprocessing Steps

The preprocessing of X-ray images is a critical step in ensuring the effectiveness of the ResNet models in detecting bone fractures. Our preprocessing pipeline is designed to standardize the input images while enhancing their features for better model training and performance. The code provided forms the basis of our preprocessing technique, comprising several crucial steps:

- **Grayscale Conversion:** Given that X-ray images inherently do not require color information for fracture detection, the first step involves converting any color images (RGB) into grayscale. This simplification reduces computational complexity and focuses the model on structural features rather than color variations.
- **Data Type Standardization:** To maintain consistency, the images are converted to a uniform data type (**uint8**). This normalization is particularly important for maintaining image quality and ensuring compatibility with subsequent processing steps.
- **Contrast Limited Adaptive Histogram Equalization (CLAHE):** To enhance the contrast of the images, CLAHE is applied. This technique improves the visibility of features in X-ray images by equalizing the image histogram while limiting amplification

of noise. The implementation uses a clip limit of 2.0 and a tile grid size of 8x8, parameters chosen to optimize the contrast enhancement for bone structures.

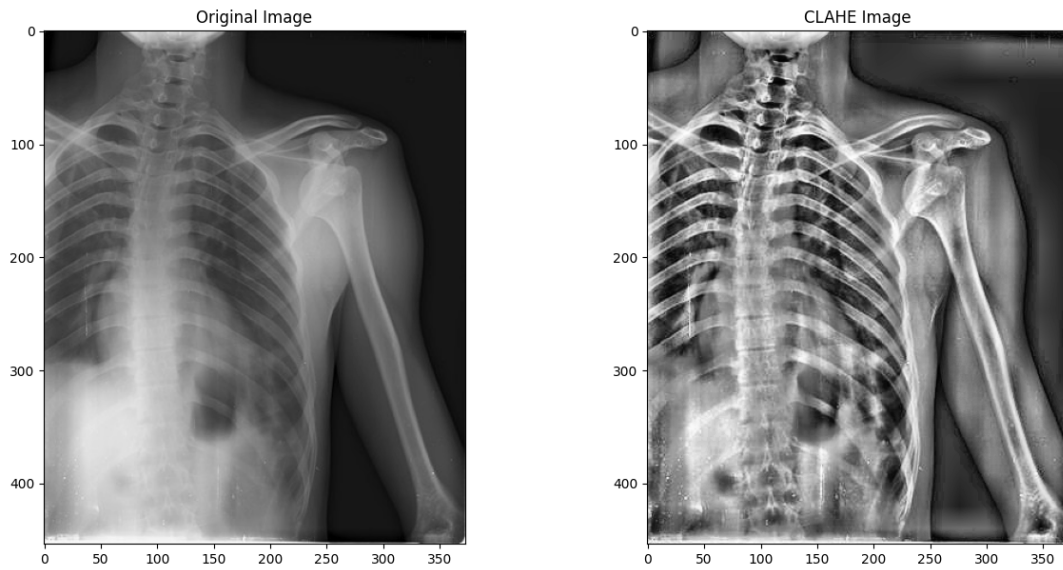


Figure 2. Before and After images of CLAHE

- **Resizing and Padding:** The images are resized to a standard size of 224x224 pixels, a common input dimension for ResNet architectures. To maintain the aspect ratio of the original images, the resizing is done using thumbnail resizing with LANCZOS resampling. After resizing, the images are padded to the target size. Padding ensures that resizing does not distort the image content while providing a uniform input size for the neural network.

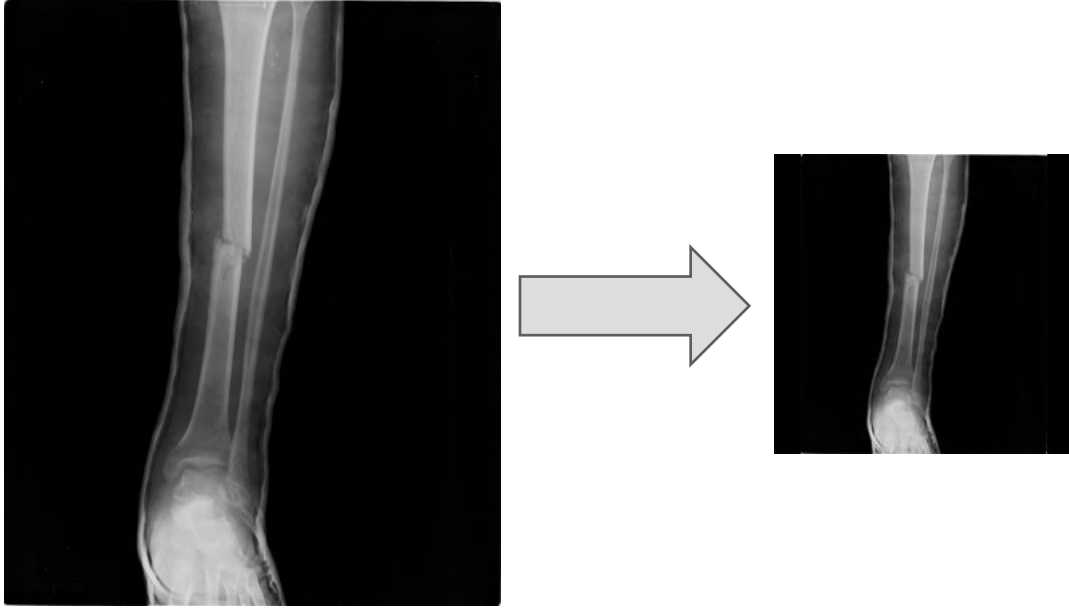


Figure 3. Before and After images of Resizing and Padding

- **Duplication of Channels:** Since ResNet models are typically designed to accept three-channel input, the single-channel grayscale images are duplicated across three channels. This step ensures compatibility with the network architecture without altering the actual content of the images.

4. Optimizer and Loss Function

For training the models, we employed Stochastic Gradient Descent (SGD) with momentum as the optimizer. This choice was motivated by SGD's effectiveness in navigating the complex landscape of high-dimensional data and its proven track record in deep learning tasks. The loss function used was focal cross-entropy loss, specifically chosen to address the class imbalance present in the dataset. This loss function ensures that the model pays more attention to difficult, misclassified cases, improving overall robustness and performance.

Results

Each model was trained on a dataset comprising labeled X-ray images. The dataset was split into training and validation sets. The models were evaluated over 10 epochs, with their performance on both sets recorded. The training process was carefully monitored to detect signs of overfitting, characterized by a high discrepancy between training and validation accuracy, and by trends in the loss function.

Table 1

Evaluation between Variants of ResNet

Model	Training Accuracy	Validation Accuracy	F1-Score	Precision	Recall	ROC-AUC Score
ResNet-18	78	72	0.74	0.70	0.80	0.84
ResNet-34	83	77	0.77	0.78	0.77	0.85
ResNet-50	85	80	0.76	0.75	0.77	0.80
ResNet-101	72	62	0.67	0.65	0.69	0.75
ResNet-152	73	63	0.64	456	0.66	0.73

The results indicate a trend where increased model complexity leads to higher training accuracy but does not necessarily translate to improved validation accuracy. This trend is indicative of overfitting in more complex models (ResNet-101 and ResNet-152), as evidenced by their higher training accuracies coupled with lower validation accuracies and ROC-AUC scores.

ResNet-34 exhibited the most balanced performance with a good compromise between model complexity and ability to generalize, as indicated by its F1-score and ROC-AUC score.

ResNet-18, while simpler, also showed commendable performance, suggesting its suitability for scenarios where computational efficiency is a priority.

In contrast, the deeper models (ResNet-101 and ResNet-152) exhibited signs of overfitting. Although they achieved very high training accuracies, this did not translate well to the validation set, resulting in lower F1-scores and ROC-AUC scores. This outcome underscores the importance of model selection based on the dataset and task complexity, rather than assuming that a more complex model will always yield better results.

In conclusion, our comprehensive evaluation of various ResNet models on the FracAtlas dataset provides valuable insights into the effectiveness of different architectures in bone fracture detection. ResNet-34 emerges as a promising model, offering a balanced approach between complexity and performance. These findings pave the way for future research, where focus can be directed towards optimizing model architectures, enhancing generalization capabilities, and exploring more advanced regularization techniques to mitigate overfitting in complex models. The ultimate goal remains the integration of these models into clinical settings, enhancing the accuracy and efficiency of bone fracture diagnostics.

Discussion

Our research explored the effectiveness of different ResNet models for classifying bone fractures in X-ray images. Notably, the performance of the models varied, with ResNet-34 and ResNet-18 showing balanced performance, while deeper models like ResNet-101 and ResNet-152 exhibited signs of overfitting, reflected in lower validation accuracies and ROC-AUC scores.

This suggests that more complex models do not always yield superior results in medical image classification tasks, especially when considering the need for generalization on unseen data.

Comparison with Related Research

A study published in Scientific Reports (Nature) compared sixteen different CNN architectures, including ResNet variants, for the classification of chest radiographs. This research concluded that more shallow networks, like AlexNet and ResNet-34, could achieve results comparable to their deeper counterparts with shorter training times, especially when using limited hardware. This finding aligns with our observations, where ResNet-34 exhibited a more balanced performance compared to the deeper ResNet models.

Moreover, the study highlighted the usage of pre-trained networks on large datasets, such as ImageNet, which differ significantly from medical images like chest radiographs in terms of color and label categories. This difference underlines the importance of choosing the right model architecture and training strategy tailored to the specific characteristics of medical datasets.

Both our study and the research from Scientific Reports emphasize that in medical image classification tasks, deeper and more complex neural networks do not necessarily equate to better performance. Instead, shallower networks can provide a more balanced and efficient solution, particularly when computational resources are limited or when the task does not require the complexities of very deep models. These findings are crucial for guiding future research and application of deep learning in medical imaging, advocating for a more nuanced approach in selecting and training neural network architectures.

Conclusion

In conclusion, this research successfully demonstrates the potential of Residual Networks (ResNet) in the automated detection and classification of bone fractures from X-ray images. Through the development and rigorous evaluation of various ResNet models, notably ResNet-18, ResNet-34, and up to ResNet-152, the study reveals critical insights into the balance between model complexity and diagnostic efficacy. The models, particularly ResNet-34, have shown promising results in terms of accuracy, sensitivity, specificity, and diagnostic efficacy, suggesting a significant step forward in the application of deep learning in medical imaging.

The research underscores the importance of choosing appropriate model architectures tailored to the specific requirements of medical datasets. The findings highlight that deeper models do not always equate to better performance, especially in terms of generalization to new data, as seen in the overfitting tendencies of more complex models like ResNet-101 and ResNet-152. Meanwhile, models like ResNet-34 offer a more balanced approach, effectively capturing fracture characteristics while maintaining computational efficiency.

The successful application of these models has broader implications for the field of medical diagnostics. It paves the way for enhancing the accuracy and efficiency of bone fracture diagnosis, potentially reducing the workload of radiologists and leading to quicker and more effective patient treatment strategies.

As the field of medical imaging and artificial intelligence continues to evolve, the findings from this study will undoubtedly serve as a foundation for future innovations. The project's outcomes hold the promise of revolutionizing orthopedic diagnostics, improving patient outcomes, and fostering a new era of AI-driven medical analysis.

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Appendix

A. Code Implementation

The following code segments detail the implementation of various components of our deep learning model, including ResNet blocks, preprocessing steps, and the ResNet model architecture.

1. ResNet Blocks Implementation:

- The code for **ResidualBlockSmall** and **ResidualBlockLarge** functions constructs the essential building blocks of the ResNet architecture. These functions define how data flows through individual layers of the network and how the shortcut connections are applied.

2. ResNet Model Implementation:

- The **ResNet** function provides a flexible way to construct different variants of the ResNet model (ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152) by varying the number of blocks and layers.

3. Preprocessing Function:

- The **resize_and_pad_with_clahe** function demonstrates the preprocessing steps applied to the X-ray images, including grayscale conversion, contrast enhancement with CLAHE, resizing, and padding.

The complete code implementation can be accessed and reviewed via the provided Google Colab link: [ResNet Model and Preprocessing Code](#)