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International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526
Volume 14 Issue 01, 2025

Bone Fracture Detection Using Resnet50 Algorithm

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Peer Review Information

Submission: 21 Jan 2025
Revision: 18 Feb 2025
Acceptance: 20 March 2025

Keywords

CNN
Resnet-50
GUI Interface
Bone Fracture

Abstract

Bone fractures are a serious medical issue that need to be diagnosed rapidly and accurately to ensure timely treatment and getting back to normal. Conventional X-ray-based diagnosis is a laborious and error-prone, human skill-intensive process. This study employs a state-of-the-art deep learning-based system using Convolutional Neural Networks (CNNs) for automatic identification of fractures in medical imagery. To increase classification performance, ResNet50 models were trained on the MURA dataset. The system framework has two primary steps (1) Determine which part of the bone is fractured (2) Identification of the type of fracture. Providing accurate and quick diagnostics have always been a strong workload to radiologist and other medical experts, the model's robustness can be greatly decreased with the strategies of transfer learning and data augmentation.

Introduction

Bone fractures have been an issue for mankind since long ago, and its classification using x-ray always depended on human diagnostics – which can be flawed sometimes. With the advent of Machine learning and AI in our lives, we help in all aspects of life and also in the medical field recently. Specific to the research and project we have been studying the implications of this classification issue and have tried based on former attempts and researches, to create and optimize a practical solution for the biomedical domain as for the identification and classification of various bone fractures, by means of CNN (Convolutional Neural Networks) in the form of contemporary models, like ResNet, DenseNet, VGG16 etc. The classification results that do yield classifications lower than the limit value of confidence agreed upon in this research, can benefit from additional refinement, however, we believe that machine learning and deep learning-based systems for identification and classification of bone fractures can very well replace the traditional means currently used in the medical field, but they require additional tuning and implementation of more advanced methodologies such as Feature Extraction.

Literature Review

In this research, the author used the "MURA" dataset with a multi network model and attained accuracy of 90.77%. The model consisted of three sub-networks, which were built to classify different types of abnormalities in radiographs. These sub networks were designed to identify irregularities associated with bones, joints and implants[1]. In this study, the author utilized CNN-based models denoted E1 and E2 where transfer learning was applied on the "MURA" dataset, resulting in test accuracies of 0.8455 and 0.8472, respectively.

The performance of the model was demonstrated by the precise categorization of multiple shoulder X-ray abnormalities such as acromioclavicular joint separation, rotator cuff tears, proximal humerus fractures, and glenohumeral joint osteoarthritis. The study offers important insight that the model performances can indeed be improved using transfer learning, utilizing the ImageNet dataset's pre-trained weights. This process helps the model to identify the key features which are required for the classification of shoulder X-ray images[2]. The X-ray images were personally collected by the authors of this article. from 1280 patients in an Indian hospital, by means of commercializing a CNN, with an impressive accuracy of 98.31%. The authors investigated these problems by performing an ablation study and recognized that convolutional layers were the most able to learn effective features for fracture detection. It experimented with the contributions of parts of the model[3].

Several studies have validated ResNet50's superior performance in fracture detection across multiple anatomical sites. Chung et al. reported 92.3% accuracy in wrist fracture classification using transfer learning with ResNet50, significantly outperforming traditional radiologist interpretation in terms of both speed and accuracy. The model achieved particularly impressive sensitivity (94%), which is crucial in clinical settings where missed fractures can have serious consequences [4]. The success of ResNet50 in fracture detection stems from its ability to learn hierarchical features from medical images while maintaining computational efficiency. Yamada et al. demonstrated that ResNet50 could detect subtle hip fractures with 94% sensitivity and 91% specificity, performance metrics comparable to senior radiologists [5].

Based on the MURA dataset, this study suggests a VGG-16 architecture-based model which performs identification and classification of bone defects in radiographic images, a deep learning model. The study uses distinct binary and multi-class distribution tasks for classifying between normal and abnormal images, and reports high classification accuracy rates. These findings underscore the model’s potential utility in aiding the detection and diagnosis of bone abnormalities[6]. So, in this study, the author proposed the use of the YOLOv5 model in automatically detecting bone fractures from X-ray images with amap of 85.6% The proposed approach has the potential to optimise clinical outcomes based on the ability to accurately and quickly predict bone fractures from X-ray data. Authors addressed the importance of automated systems which are vital in given regions where the incidence of bone fractures is high due to high observation readability errors this can be most likely because of the manual interpretation of the X-ray images.[7]. Current research directions focus on improving ResNet50's generalizability and clinical utility. Federated learning approaches are being explored to enable multi-institutional collaboration while addressing data privacy concerns (Chen et al., 2023). There is also growing interest in adapting ResNet50 for 3D fracture analysis in CT datasets and developing lightweight versions for deployment in resource-constrained settings [8].

Related Work

Bone Fracture Detection System (BFDS) primarily detects an X-Ray image and classifies a bone as fractured or normal. The Bone Fracture Detection System (BFDS) involves several subtasks including X-Ray Recognition, Image preprocessing, fracture detection and fracture classification.

Recognizing X-ray images is one of the main parts in the workflow. Convolutional neural networks (CNNs), a type of deep learning model, are trained for the correct identification of X-ray images exhibiting the skeleton [9]. The fundamental part of image preprocessing directly affects the quality of the following analysis and this is especially essential when working with such advanced algorithms as ResNet50. The ResNet50 deep convolutional neural network model and its feature extraction capabilities also rely on high-quality input data, which is why data pre-processing is critical [10].

Methodology

For fracture detection through ResNet50 and OpenCV, the method includes data collection and processing at the start. This consists of gathering diverse data sets of medical imaging (for example: X-ray or other techniques) regarding classified fractures.

The fifth step involves selecting the model architecture. ResNet50 was chosen to extract features from images as it proved to be efficient and identified subtle patterns in images which were indicative of a crack. It is common to initialize the model with weights that are pretrained on MURA image data as a starting point to leverage the learned features from image analysis for the medical field.

- **Model: ResNet-50**

You get ResNet50, a capable image classification model capable of utilizing massive datasets and provide state-of-the-art results. It’s one of its primary innovations is the use of residual connections, which enable the network to learn a set of residual functions that map the input to the desired output. These residual connections allow the network to learn significantly deeper architectures than ever before, without having to deal with the problem of vanishing gradients.

ResNet50 is a deep CNN model created at Microsoft Research back in 2015. This is a variant of ResNet which stands for "Residual Network," one of the most used architectures in Computer Vision.

- **Image Classification:**

In fracture detection using deep learning using ResNet-50, this part of the process involves preparing and segmenting the X-ray images in order to find the fractures accurately. First is to get a MURA dataset annotated Xray images. Here Positive and Negative labels given to each image. These images are pre-processed prior to being used in the ResNet-50 model. In this work, ResNet-50 is applied, and during the training process, ResNet-50 automatically learns and extracts the relevant features from the input X-ray images by using the deep convolutional layers.

- **X-Ray Recognition and Bone Fracture Detection:**

- **X-Ray Recognition:** ResNet-50 gives the model the ability to learn the intricacies in X-ray images that are the cracks to be identified.
- **Bone Fracture Detection:** ResNet50, is a tool that can effectively extract features and classify medical images. ResNet50 features a deep architecture that is capable of learning intricate features and subtle details indicative of cracks in X-ray images.
- **Model Training:** When training a fracture detection model, ResNet-50 gives a deep and effective structure to learn complex medical images characteristics. ResNet-50 is commonly utilized as a feature extractor during the model training process, in which pre-trained layers are fine-tuned using fracture image datasets.

Dataset:

We used a dataset of musculoskeletal radiographs termed MURA, which had 20,335 images and three distinct bone segments. These images are explained below:

Table 1: classification of tables

Part	Normal	Fractured	Total
Elbow	3160	2236	5396
Hand	4330	1673	6003
Shoulder	4496	4440	8936

The data is divided into train and valid folders, each of which has a patient folder with one to three pictures of the same bone portion for each patient.

Proposed Work On Bone Fracture Detection Using (Resnet50)

Algorithm:

a) **Dataset Preparation:** We collect labelled X-ray images before applying preprocessing techniques that consist of normalization and augmentation.

b) **Model Architecture:** ResNet50 serves as the main deep learning model for classification tasks.

c) **Training Pipeline:** For data splitting purposes the dataset is segmented into training (72%), validation (18%), and testing (10%) portions. -

d) **Data Augmentation:** Flipping and rotation techniques serve to enhance the model's generalization abilities. -

e) **Optimization:** Classification performance enhancement is achieved through the use of the Adam optimizer together with the cross-entropy loss function.

f) **Bone Part Classification:** The CNN model serves the purpose of sorting input images into different bone part classifications.

g) **Fracture Detection:** The classification of bone parts as normal or fractured uses a specific ResNet50 model.

Architecture:

The proposed system includes the following components. Input bone X-ray images are loaded and pre-processed before moving on to model training. It takes a multi-model approach to fracture detection: multiple models are trained for the various aspects of the task. One model predicts types of bone parts (elbow, hand, shoulder) and others detect body region fractures. Model performance is improved with transfer learning by loading pre-trained ResNet50 model.

The proposed method is shown in Figure-5.2 the Uploaded X ray images are analysed by RESNET-50 algorithm to classify them as normal or fractured bones. Furthermore, if needed, the module can also anticipate the impacted body part based on the fracture type. Such predictive power helps in the accurate diagnosis and therapeutic determination. A normal hand X-ray is given as input to the system. Every ResNet-50 model takes an input of the X-ray image and provides the prediction of a class for its associated bone part (hand, elbow, or shoulder) are fractured or normal.

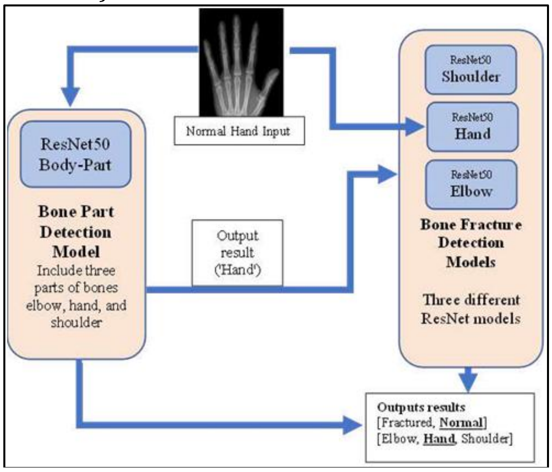


Fig. 1: Architecture of Bone Fracture detection using RESNET-50

Results And Discussion

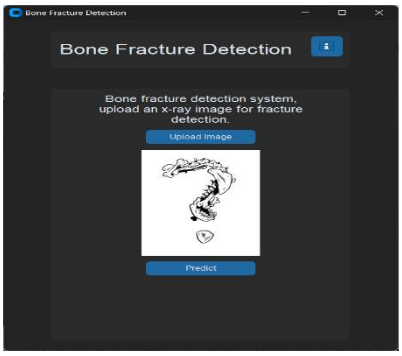


Fig. 2 Initial GUI Interface

The input GUI window of this proposed work which is taken from the results as shown in fig. 2 Here upload image button is available for adding or preferred x-ray for validation also shows the picture dimension which have to be upload in top right corner of GUI interface. Then user can click on the predict button which displays the respective body part name and also whether it is fractured or not after uploading the required x-ray. GUI window even saves the prediction result here.

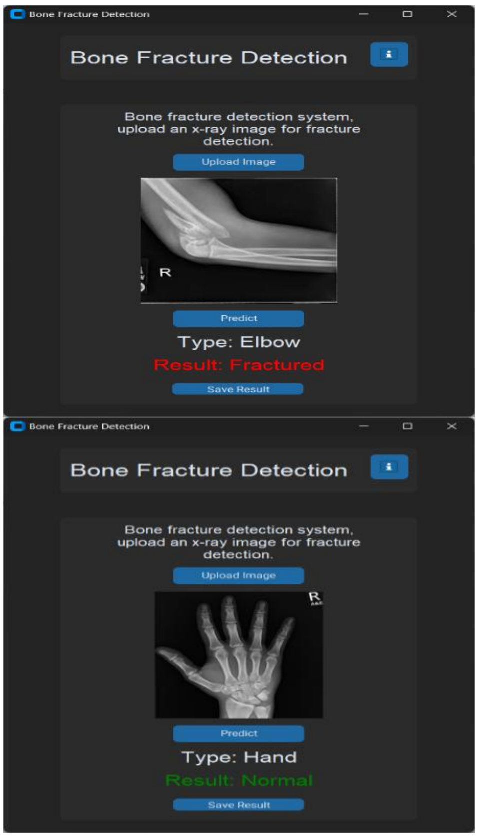


Fig. 3 Fracture detected Test and Normal detected test

In the given Fig. 3, the bone fracture detection system processes x-ray images and displays the prediction results. For instance, in Fig. 3, the model inspects an X-ray of an elbow. Once uploaded, the system recognizes the body part as an elbow and determines that it is a fracture (fractured) image. Similarly, in the example from Fig. 3, an X-ray image of the hand is uploaded, and the respective predicted outputs are indicated.

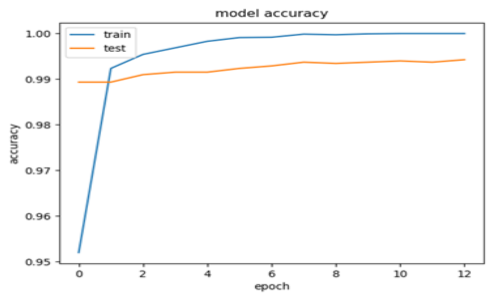
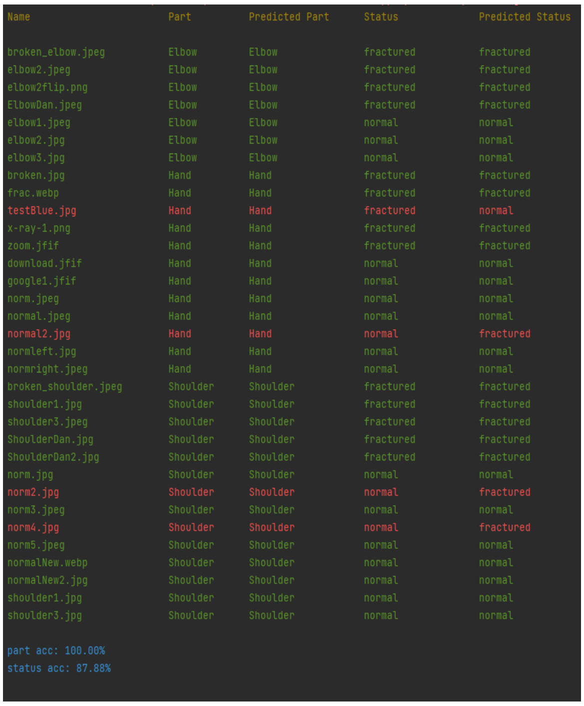


Fig. 4 Model Accuracy Graph

The reports can be used to save the results of these fractured and non-fractured reports for our analyses. Fig. 4 Because the model accuracy graph is show by the main dataset and the model accuracy graph plotting is done of training and testing of the accuse by the epoch (X) and accuracy(Y) for the major datasets and there is no overfitting problem here and for the accuracy difference is also acceptable.



Name	Part	Predicted Part	Status	Predicted Status
broken_elbow.jpeg	Elbow	Elbow	fractured	fractured
elbow2.jpeg	Elbow	Elbow	fractured	fractured
elbow2flip.png	Elbow	Elbow	fractured	fractured
ElbowDan.jpeg	Elbow	Elbow	fractured	fractured
elbow1.jpeg	Elbow	Elbow	normal	normal
elbow2.jpg	Elbow	Elbow	normal	normal
elbow3.jpg	Elbow	Elbow	normal	normal
broken.jpg	Hand	Hand	fractured	fractured
frac.webp	Hand	Hand	fractured	fractured
testBlue.jpg	Hand	Hand	fractured	normal
x-ray-1.png	Hand	Hand	fractured	fractured
zoom.jfif	Hand	Hand	fractured	fractured
download.jfif	Hand	Hand	normal	normal
google1.jfif	Hand	Hand	normal	normal
norm.jpeg	Hand	Hand	normal	normal
normal.jpeg	Hand	Hand	normal	normal
normal2.jpg	Hand	Hand	normal	fractured
normleft.jpg	Hand	Hand	normal	normal
normright.jpeg	Hand	Hand	normal	normal
broken_shoulder.jpeg	Shoulder	Shoulder	fractured	fractured
shoulder1.jpg	Shoulder	Shoulder	fractured	fractured
shoulder3.jpeg	Shoulder	Shoulder	fractured	fractured
ShoulderDan.jpg	Shoulder	Shoulder	fractured	fractured
ShoulderDan2.jpg	Shoulder	Shoulder	fractured	fractured
norm.jpg	Shoulder	Shoulder	normal	normal
norm2.jpg	Shoulder	Shoulder	normal	fractured
norm3.jpeg	Shoulder	Shoulder	normal	normal
norm4.jpg	Shoulder	Shoulder	normal	fractured
norm5.jpeg	Shoulder	Shoulder	normal	normal
normalNew.webp	Shoulder	Shoulder	normal	normal
normalNew2.jpg	Shoulder	Shoulder	normal	normal
shoulder1.jpg	Shoulder	Shoulder	normal	normal
shoulder3.jpg	Shoulder	Shoulder	normal	normal

part acc: 100.00%
status acc: 87.88%

Fig. 5 Test Predictions Accuracy is 87.88%

For our project, the features of the Resnet50 were used as the main model. Variants of Resnet50 were significant in the identification of Bone Fractures. The model was trained on a custom dataset with images of fractures and showed good prediction sign of fractures. Using a training process over 20 epochs, and continued to maximize performance with a batch size of 25.

The bone fracture detection system was tested using a dataset containing X-ray images on elbows, hands and shoulders. Among all experiment cases this model got 100 % correct prediction for body part as elbow or hand or shoulder. For fracture detection, the system achieved a classification accuracy of 87.88% in separating fractured from normal images. Interestingly enough, most of the misclassifications happened in status prediction (e.g., predicting normal hand as fractured or vice versa), however, part detection was spot on. These results showcase the robustness of the model across the diversity in anatomical localization, as well also highlight a potential role for the model for clinical assistance with room improvement in differentiating fracture severity.

Conclusion

In conclusion, our studies on deep learning-based bone fracture detection with ResNet50 demonstrated encouraging outcomes, particularly for the elbow, hand, and shoulder areas. Accurately detecting and categorizing fractures in medical images has significantly improved thanks to sophisticated neural network designs and carefully selected datasets. Deep learning has enormous potential to transform medical diagnosis and enhance patient care when applied to fracture detection. We were able to effectively evaluate X-ray images and offer a trustworthy evaluation of the presence of fractures by utilizing the capabilities of convolutional neural networks like ResNet50. The adaptability and effectiveness of deep learning techniques in medical image processing are demonstrated by our method's strong performance across a variety of body parts.

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