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# Strategies for Rapid Bone Breakage Prediction using Deep Learning

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## Abstract

Because of their prevalence, bone diseases may cause a broad variety of musculoskeletal ailments. Worldwide, an estimated 1.71 billion individuals are impacted by musculoskeletal problems. Bone diseases are common and include musculoskeletal fractures, osteoarthritis of the knee, and femoral neck injuries. The opposite is true for missed fractures; they are a common prognostic failure in emergency situations. Consequently, the care and treatment of patients becomes more convoluted and takes longer. There is a lot of excitement right now about the possibility that Deep Learning (DL) and Artificial Intelligence (AI) might aid doctors in detecting bone fractures. Research in orthopedics and traumatology has shown that DL may be helpful in diagnosing diseases and fractures using radiographs. Several methods for bone categorization have been examined and contrasted in this work. We employ Inception-v3, VGG16, Densenet-121, and Resnet-50 for wrist bone recognition and segmentation. Densenet-121, Inception-v3, and Resnet-50 are used for elbow bones. In the trials, two datasets—the Kaggle dataset and the MURA dataset—are employed. The experimental findings reveal that Densenet-169 outperformed the other models on the MURA dataset and Inception-v3 on the Kaggle dataset. due to the vast variety of bone types, computer-assisted anomaly detection for bones is now crucial. Medical imaging using X-rays is the gold standard for diagnosing abnormalities in bones, especially after a fracture. In order to make important decisions about the diagnosis, medical experts rely on X-ray images. If the bone anomaly is misdiagnosed, it might lead to ineffective medical treatment, higher patient discontent, and expensive legal proceedings. To that end, it is considered crucial to correctly diagnose these anomalies and treat them as needed. Recent years have seen a deluge of scholarly publications devoting space to the topic of developing computer-aided approaches for bone fracture detection. The bulk of past research only considered one bone because of the vast variety of bone defects and the noticeable differences in bone structure. Consequently, it would be completely impractical to cover every bone in the human body with such a large number of devices.

Keywords— Medical imaging, Deep Learning, Resnet-50, VGG16, Densenet-121, Inception-v3, VGG16

## INTRODUCTION

Many different areas of medicine have made use of medical imaging techniques. The X-rays domain is among the best known. Thanks to advancements in radiation technology and computer image processing, digital X-ray imaging machines have become more popular in many medical contexts. Doctors are able to discover anomalies in human bones with the assistance of computer-aided diagnostics. The defect may form in any bone in the human body, which makes diagnosing bone abnormalities a very difficult task. Reason being, two bones in the upper extremities—the elbow and the wrist—are the focus of this article. In this method, there are two steps. In the first step, X-ray pictures are used to identify any abnormalities or normalcy in the bone. Stage 2 involves determining the kind of atypical bone fracture. When it comes to wrist bones, the given method employs Inception-v3, VGG16, Densenet-121, and Resnet-50. When it comes to elbow bones, it employs Resnet-50, Inception-v3, and Densenet-121. The MURA dataset, which was used in the first phase, and a another dataset from Kaggle, which includes different kinds of wrist and elbow fractures, which was utilized in the second phase. What follows is an outline of the rest of the paper: Section 2 provides an overview of the relevant literature. The

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suggested approach is detailed in Section 3. Section 4 presents the experimental outcomes. Section 5 concludes the paper.

## RELATED WORK

There have been a number of recent studies that have shown the ability to detect bone anomalies, namely fractures, and even to determine the specific kind of fracture. A brief synopsis of the prior literature is given in this section. In order to categorize anomalies in the top seven bones, X-ray bone abnormality detection using Mobile-Net Networks is suggested in [1]. They demonstrated a two-step process for abnormality identification in bone X-rays using the Mobile-Net convolutional neural network (CNN). The first use of Mobile Net is to determine whether X-ray pictures are normal or pathological. Using data from a second Mobile-Net model, the second step goes even farther into categorizing the areas of interest from the first stage as different kinds of anomalies. In order to enhance the X-ray pictures, the researchers use a number of pre-processing techniques. Some of these methods include enhancing data to increase the variety of the training dataset, shrinking photographs, and normalizing pictures to scale pixel values. To add more training examples, data augmentation methods include picture rotation, translation, and scaling. With the MURA dataset, we were able to attain an average accuracy of 73.42% for all seven bones, with the Humerus reaching an impressive 86.52%. One study that utilized the MURA dataset to find abnormalities in X-ray bone scans was Solovyova et al. [2]. To identify anomalies in X-ray scans of the bones, they used a method based on deep learning. A huge database of musculoskeletal radiographs is used in the MURA dataset.

This is the suggested approach uses a fully connected layer to categorize X-ray images as normal or abnormal, and then uses a pre-trained ResNet-50 model to extract features. Several data augmentation strategies were also evaluated by the authors in an attempt to improve the model's functionality. With the proposed method, X-ray pictures of aberrant bones may be identified with an accuracy of about 80%. In order to automatically detect wrist fractures from posteroanterior and lateral radiographs, Ebsim et al. [3] put forth a method. They used a deep learning-based method to automatically detect wrist fractures from lateral and posteroanterior radiographs. Of the 3,718 wrist radiographs reviewed, 2,641 were found to have a fracture and 1077 were found to be negative. To automatically extract properties from input radiographs, the suggested technique employs a convolutional neural network (CNN) model. Next, the model uses a fully connected layer to categorize the radiographs as either showing a wrist fracture or not. Additionally, the researchers conducted tests to evaluate the impact of data augmentation methods on the model's performance and to compare the suggested method to current state-of-the-art models. The findings showed that the suggested method outperformed previous state-of-the-art models with an accuracy of 91%. In order to assess bone abnormalities such as infections and fractures, Abhilash et al. [4] used a Dense-Net Convolutional Neural Network for Abnormality Detection from X-Ray Bone Images. With this dataset, the researchers trained and tested their Dense Net CNN, and it achieved a total anomaly recognition accuracy of 94.7%. After developing their Dense-Net CNN, the researchers tested it against existing state-of-the-art methods for bone scan anomaly detection and found that it performed better. The study's findings, taken as a whole, point to the potential clinical diagnostic and therapeutic uses of Dense-net CNNs for anomaly detection in X-ray bone images.

## PROPOSED METHOD

This research suggests a two-stage approach to classifying two bones (the elbow and the wrist), as seen in Fig. 1. Finding and labeling abnormalities in the bone (whether they be normal or pathological) is the job of the first stage. Stage 2 is to determine the kind of elbow fracture [8, 9, 10] and wrist fracture [5, 6, 7]. After that, there is a classifier for every bone that can identify the kind of fracture. Subsequent sections elaborate on the dataset and the steps of the proposed methodology in detail. Table A. The MURA dataset contains 9,067 normal picture samples and 5,915 aberrant ones [11, 12]. In this case, we utilize the wrist dataset (3697 photos) and the elbow dataset (1912 images). Images of the elbow and wrist make up the kaggle dataset. Complete, incomplete, and dislocation fractures make up the three main categories in the Kaggle dataset. The wrist data consists of 602 training photos and 117 testing images [13]. Furthermore, the elbow data contains 896 training photos and 150 testing images [14]. We zeroed down on the wrist and elbow datasets because finding anomalies in these bones may aid in correct diagnosis, treatment planning, and rehabilitation; also, these bones are widespread and clinically essential. Therefore, while it is possible to study other

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bones of the upper extremities, there are unique benefits to studying the wrist and elbow from both a scientific and therapeutic perspective. A crucial part of every data science or deep learning effort is the preprocessing step (B.). It may help guarantee that the data is understandable, properly prepared, and applicable to modeling and analysis. When it comes to machine learning, data preparation is essential for a number of reasons, including better accuracy, less likelihood of over-fitting, easier modeling, and more interpretability. Artificially increasing the quantity and variety of a training dataset is the goal of image augmentation, a method used in computer vision and machine learning. Image augmentation is a procedure that tries to improve machine learning models' performance and generalizability by adding variations and increasing the amount of training data that is available. First, the photographs were all cropped to 224 × 224 x 3 pixels. Then, several augmentation techniques were used, including random contrast, horizontal flipping, random gamma, and random brightness. Section C: Feature Recognition and Extraction Starting with the wrist and elbow, we determine whether they are normal or aberrant. For the wrist, we utilize Inception-v3, VGG16, Densenet-121, and Resnet-50; for the elbow, we use Resnet-50, Inception-v3, Densenet-121, and Densenet-169: a variety of deep learning approaches. Classification of images is accomplished using the Inception-v3 deep learning model. It builds on the original Inception architecture, which tackled the problem of deep neural networks' computational efficiency and model size. We opted for this model because it delivers excellent results while making good use of computer resources and causing just a little increase in calculation load. Version 3 of Inception

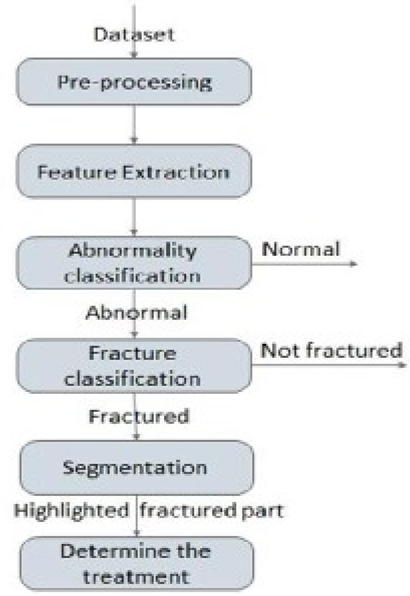


Fig.1. System architecture.

multi-scale feature extraction inception modules, which are blocks of layers, different filter widths, and pooling layers. In order to provide a more accurate representation of the input picture, these modules are built to extract characteristics at various spatial scales and combine them. Additionally, regularization methods like dropout and batch normalization are used to curb over-fitting and enhance generalization capabilities. A soft-max activation function generates the classification outputs in the network's last layer. One design of deep convolutional neural networks (CNNs) is Densenet-169. The "Densely Connected Convolutional Network" configuration, which goes by the acronym "Dense-Net," is characterized by a feed-forward relationship between every layer of the network. Building on Dense-Net principles, DenseNet-169 design adds depth and intricacy. Four thick blocks, each with several layers of densely linked blocks, make up the DenseNet-169 design. Part of the first block are the convolutional and max pooling layers. In a dense block, each layer is connected to every layer before it using convolutional neural networks. By facilitating information flow throughout the network, dense connections lower the number of parameters required to train the model, which in turn improves accuracy and decreases the likelihood of over-fitting. The last layer of the network is a global average pooling layer that combines all of the feature vectors from the preceding layers into one.

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This vector is then used to train a fully connected layer that uses a soft-max activation function to get the resultant classification. Identifying the kind of fracture—complete, incomplete, or dislocation—is the second step in classifying aberrant bones. We use a deep convolutional neural network (CNN) architecture called Resnet-50 model here. The networks make use of the starting weights from the Image-Net dataset. The acronym "Res-Net" means "Residual Network," while the number 50 represents the total number of network layers. There are a total of fifty layers in the ResNet-50 design, including convolutional layers, batch normalization layers, activation functions (often ReLU), and fully linked layers. Stronger representation capacity and improved classification accuracy are associated with deeper hierarchies in the ResNet-50 architecture. Section D: Dividing Figure 2 shows the segmentation of the output picture after the two-stage classification process. To determine which parts of a picture or feature map are most important for a certain classification judgment made by a neural network, we utilized a computer vision method known as Gradient weighted Class Activation Mapping (Grad-CAM) [15]. Grad CAM takes the output gradient information from a neural network and applies it to a given class; this information is then used to create a class activation map that draws attention to the parts of the input picture that are most relevant to the classification decision.

## DATA FROM CASE STUDIES

Normalization, horizontal flipping, and random contrast are some of the preprocessing steps used to prepare the MURA dataset. Identifying normal or pathological bone is the goal of the first round of tests. But the second round of tests is done to determine the kind of atypical bone fracture. A. Phase 1 (spotting abnormalities) outcome The wrist bone is segmented using a variety of algorithms, including Resnet-50, VGG16, Densenet-121, and Inception-v3. Densenet-121, Resnet-50, Inception-v3, and Densenet-169 are used for the elbow bone. You can see how well the recognition techniques worked with the MURA dataset in Table I. After comparing several models, the findings reveal that Inception-v3 obtained the greatest accuracy at 84% for the wrist bone and that the Densenet-169 model earned the best accuracy at 86% for the elbow bone. According on the MURA dataset, these two models fared better than the others. The confusion matrix of segmenting the wrist bone using Inception-v3 is shown in Figure 3. The recall, accuracy, and F1-score for segmenting the wrist bone using Inception-v3 are shown in Table II. The confusion matrix of the elbow bone segmentation using Densenet-169 is shown in Figure 4. For Densenet-169, the results for elbow bone segmentation are shown in Table III, along with recall, precision, and F1-score. Phase 2 (identification of fracture types) result (B) The Kaggle dataset features a variety of approaches to wrist bone segmentation, including VGG16, Densenet-121, Le-net, and

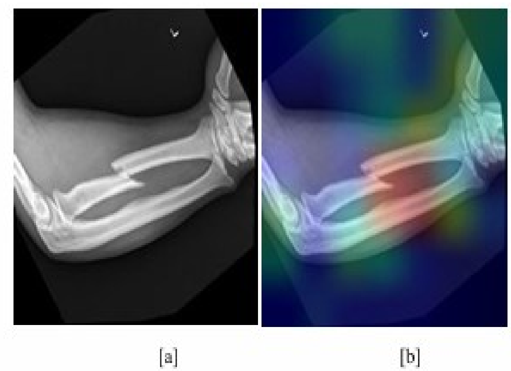


Fig. 2. Image segmentation: (a) image before grad-cam and (b) image after applying grad-cam to highlight fracture.

TABLE I. RESULTS OF ABNORMALITY DETECTION USING MURA DATASET.

| Bones | Models | Accuracy |
|---|---|---|
| Wrist | Resnet-50 | 68% |
| | VGG16 | 72% |
| | Densenet-121 | 76% |
| | **Inception-v3** | **84%** |
| Elbow | Resnet-50 | 65% |
| | Densenet-121 | 73% |
| | Inception-v3 | 83% |
| | Densenet-169 | 86% |

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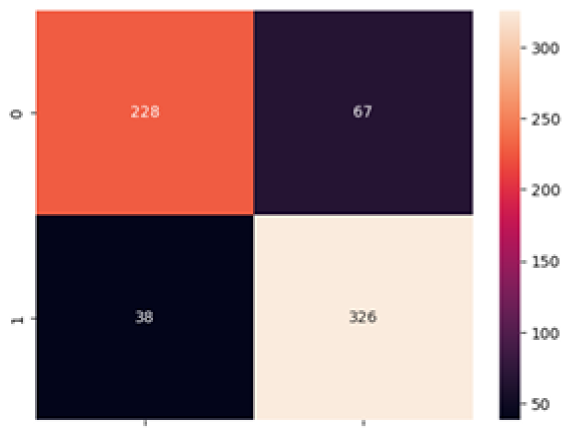


Fig. 3 The confusion matrix of using Inception-v3 to segment the wrist bone.

TABLE II. THE RECALL, PRECISION AND F1-SCORE FOR USING INCEPTION-V3 TO SEGMENT THE WRIST BONE.

| | recall | precision | f1-score | support |
|---|---|---|---|---|
| class 0 | 0.77 | 0.86 | 0.81 | 295 |
| class 1 | 0.90 | 0.83 | 0.86 | 364 |
| accuracy | | | 0.84 | 659 |

The Kaggle dataset uses Resnet-50, Densenet-121, and VGG16 for the elbow bone. Table IV provides a summary of the findings for detecting fracture types in each bone individually. When it came to segmenting bones and wrists from the Kaggle dataset, Resnet-50 outperformed the other algorithms. Figure 5 displays the confusion matrix for the Kaggle dataset when the wrist bone is segmented using Renet-50. The recall, accuracy, and F1-score for segmenting the wrist bone using Renet-50 are shown in Table V. The confusion matrix for segmenting the elbow bone in the Kaggle dataset using Renet-50 is shown in Figure 6. Table VI displays the results of the recall, precision, and F1-score for the elbow bone segmentation using Renet-50.

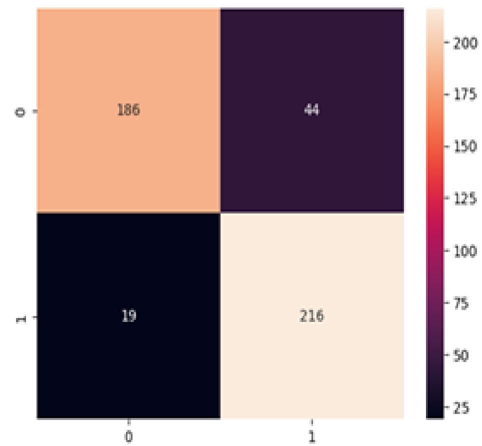


Fig. 4. The confusion matrix of using Densenet-169 to segment the elbow bone.

TABLE III. THE RECALL, PRECISION AND F1-SCORE FOR DENSENET 169TO SEGMENT THE ELBOW BONE.

| | recall | precision | f1-score | support |
|---|---|---|---|---|
| class 0 | 0.81 | 0.91 | 0.86 | 230 |
| class 1 | 0.92 | 0.83 | 0.87 | 235 |
| accuracy | | | 0.86 | 465 |

TABLE IV

RESULTS OF FRACTURE TYPE DETECTION USING KAGGLE DATABASE.

| Bones | Models | Accuracy |
|---|---|---|
| Wrist | VGG16 | 54% |
| | Densenet-121 | 64% |
| | Le-net | 56% |
| | Resnet-50 | 92% |
| Elbow | VGG16 | 55% |
| | Densenet-121 | 62% |
| | Resnet-50 | 91% |

## CONCLUSION

There are two parts to this method. In the first, we utilize the MURA dataset to test several convolutional neural network (CNN) models; they include the Inception-v3 network for the wrist dataset and the Densenet-169 network for the elbow dataset. In the second step, the kind of fracture is identified. Using the MURA dataset, we were able to attain an accuracy of 84% for the wrist and 86% for the elbow bones. In addition, the wrist bone attained 92%

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accuracy and the elbow bone 91% accuracy while utilizing the Kaggle dataset. The study tested two of the seven bones that make up the upper limb—the wrist and the elbow—rather than the one bone that had previously been the subject of inquiry.

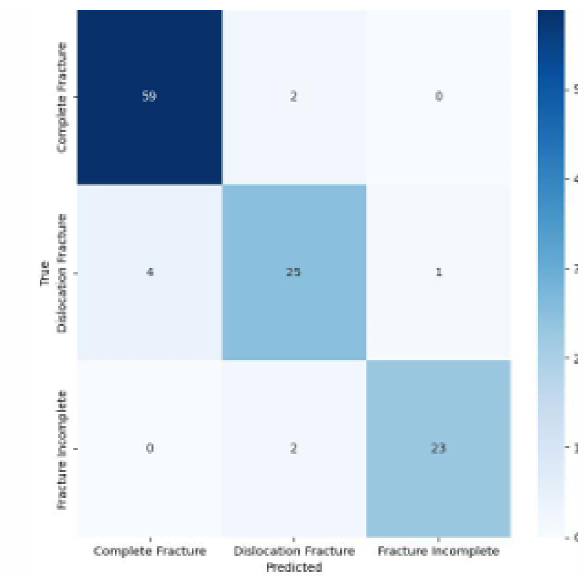


Fig. 5. The confusion matrix of using Resnet-50 to segment the wrist bone in the Kaggle dataset.

TABLE V. THE RECALL, PRECISION AND F1-SCORE FOR USING RESNET-50 TO SEGMENT THE WRIST BONE IN THE KAGGLE DATASET.

TABLE V. THE RECALL, PRECISION AND F1-SCORE FOR USING RESNET-50 TO SEGMENT THE WRIST BONE IN THE KAGGLE DATASET.

| | recall | precision | f1-score | support |
|---|---|---|---|---|
| Complete Fracture | 0.97 | 0.94 | 0.95 | 61 |
| Dislocation Fracture | 0.83 | 0.86 | 0.85 | 30 |
| Fracture Incomplete | 0.92 | 0.96 | 0.94 | 25 |
| accuracy | | | 0.92 | 116 |

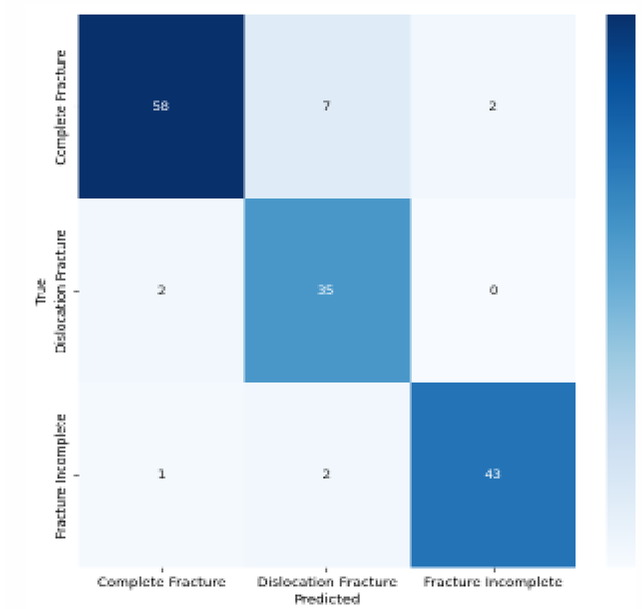


Fig. 6 The confusion matrix of using Resnet-50 to segment the elbow bone in the Kaggle dataset

TABLE VI. THE RECALL, PRECISION AND F1-SCORE FOR USING RESNET-50 TO SEGMENT THE ELBOW BONE IN THE KAGGLE DATASET.

| | recall | precision | f1-score | support |
|---|---|---|---|---|
| Complete Fracture | 0.87 | 0.95 | 0.91 | 67 |
| Dislocation Fracture | 0.95 | 0.80 | 0.86 | 37 |
| Fracture Incomplete | 0.93 | 0.96 | 0.95 | 46 |
| accuracy | | | 0.91 | 115 |

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