OPEN ACCESS
Global Journal of Research in Engineering & Computer Sciences
ISSN: 2583-2727 (Online)
Volume 06 | Issue 04 | July-August | 2026
Journal homepage: https://gjrpublication.com/gjrecs/
Research Article

Bone Fracture Detection System Modelusing Deep Learning Techniques for Densenet 169 Architecture

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DOI: 10.5281/zenodo.21282642 **Submission Date: 25 May 2026 | Published Date: 09 July 2026**

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Abstract
Bone fractures are a common medical issue that costs a lot of money and resources to treat and monitor. The government makes significant annual investments in X-ray machines, radiologists, and medical personnel to enhance patient care. However, the doctor or radiologist must manually identify the fracture after taking the X-ray scan. Digital radiography images today are produced by sophisticated scanners with excellent resolution and detail. Nevertheless, even though we could use computer vision techniques to automate or accelerate the process, we are not making use of these vast volumes of data to enhance the way we diagnose. Convolutional neural networks (CNN) and deep learning in general were introduced in recent years, and their ongoing development has completely changed the state of the art in computer vision tasks for a wide range of issues by presenting new model architectures, and training methods, as well as development and research frameworks. Deep Learning approaches, however, depend on the quality and volume of the data, even if the models and the entire technique are excellent. Few available public radiological imaging datasets are large enough to produce adequate findings for real-world data, always considering the risk of prediction error while dealing in a medical domain. MURA is a database that was made available by Stanford University for testing purposes with the target of achieving the best model for detecting bone abnormalities. Our research mainly focuses on the advancement in medical imaging technologies targeting the identification of fractures at the level of experts for improving health care access. We used Python, as a programming tool, the CNN model, and densenet 169 architecture, to process images and implement the model for bone abnormality detection. The proposed model follows a feed-forward network resulting in a good accuracy rate of 85.65%.

Keywords: *Deep learning, X-ray, Desent 169 Architecture, Convolutional neural networks (CNN).*

I. Introduction

Currently medical image processing is a significant research area that is acquiring far-reaching acknowledgment in the medical care industry because of advancements in technology and software. The fracture occurs when a severe force disburses against a bone that is tough than the bone can structurally resist. But it can also be related to the bones' weakening due to some diseases such as osteoporosis, cancers, or osteogenesis imperfecta, commonly known as bone disease. These fractures caused by medical conditions are known as pathological fractures. However, new trends and technology in radiology have advanced the diagnosis and treatment of many diseases (Ismael et al., 2020).

II. Literature review

Bone fracture: Bone fractures are a frequent issue brought on by pressure, osteoporosis, and accidents. Bone is a hard component that supports the entire body. As a result, bone fracture is now considered a serious issue. In computer-aided diagnosis systems, bone fracture detection using computer vision gets more and more crucial as a way of minimizing the labor of the physician or orthopedist.

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TYPES BONE FRACTURE

The different types of fracture include:

1. Traverse fracture: The break is in a straight line across the bone.
2. Linear fracture: The break that runs parallel to the bone's main axis.
3. Oblique fracture: The break that runs diagonally across the bone.
4. Spiral fracture: It occurs when a long bone is twisted (rotated) with force. It is also known as torsion fracture.
5. Greenstick fracture: An incomplete fracture in which the bone is partially broken and partially bent.
6. Comminuted fracture: In this type, the bone is shattered into small pieces and this kind will take more time to heal. (Setty et al., 2020)

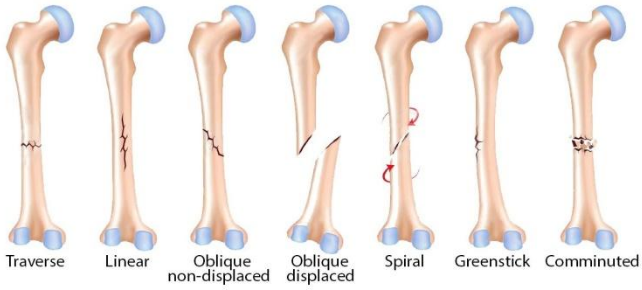

Fig. 1. Types of Bone Fracture (Setty et al., 2020)

A. Computer Vision

To understand and talk about this thesis's literature, we have to start from Artificial Intelligence (AI) basics. AI describes the ability of a machine to carry out operations that are typically performed by humans since they need for human intelligence andjudgment. Among the multiple fields grouped under the Artificial Intelligence discipline, we have Machine Learning (ML), the subset of AI algorithms that are able to perform complicated tasks learning from the data instead of using pre-defined rules or heuristics.

This work focuses on methods that take images as their input instead of raw data, which we can classify into the ML sub-category of Computer Vision (CV). We can describe CV as the field of AI that focuses on extracting features from images to identify, discriminate, detect, or classify different objects from images. The most crucial step in a classical CV approach is the feature extraction process, probably more or at least as necessary as the model itself, as the quality of the data and the features that we can extract from it will significantly influence the resulting performance. Feature extraction consists of deciding which characteristics of an object are essential to perform the desired task, and we must implement and use the algorithms that allow extracting these. It can be trivial for a few tasks, but for more advanced problems such as ours, this would require a large team of people with some domain experts to identify these essential features.

We can use several common and well-known methods to extract features, always depending on the type of image, domain, and task that we aim to perform. Some of them are based on edge detection by convolving kernel operators such as the Sobel or Canny operators [1], corner detection with Harris Corners [2], and blob detectors with derivatives with respect to the position (Laplacian or Difference of Gaussians (T. Lindeberg,2016). There are also feature description methods that usually combine the extraction and description of the features, such as SIFT (D. G. Lowe,2011) or Histogram of Gradients (N. Dalal and B. Triggs,2012).

B. Deep Learning

Deep Learning (DL) is a sub-discipline of Machine Learning. The main idea that characterizes DL inside ML is the Neural Network, a model that is able to detect and extract the best features for the target task automatically, without the necessity to involve a previous step to the model training of feature extraction.

In Deep Learning, the feature extraction process is merged with the learning process. Therefore, the selection is trainable, and the model itself is able to decide which features to use without having to choose which attributes should be extracted. The only drawback of this is that it requires much larger training data sets, a comprehensive data pre-processing pipeline, and an empirical hyper-parameter tuning process.

C. Artificial Neural Networks

Artificial neural networks, also known as neural networks or just networks, are computer algorithms that are loosely based on the biological neural circuits which make up animal brains. Numerous layers of neurons make up these artificial neural networks, where the relationships between the neurons in one layer and those in the layer that follows above are predetermined. Sample generation and data categorization or prediction are two learning tasks that can be applied to neural networks, which are representation learning techniques. A neural network is depicted for a binary classification

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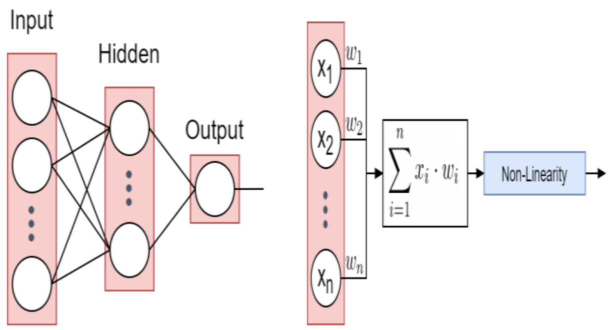
task in Figure 2.1a. Depending on the problem and the data's codification, The properties of a data row in tabular data, the pixels of a picture, or the encoding of a word are just a few examples of the many diverse forms that the input might take. For the model to make the final prediction, the intermediate layers—hidden layers with internal representations that are largely incomprehensible to humans—must contain abstract information. In the figure 2.1 b, there is only one concealed layer, but there can theoretically be any number of layers. The final layer, known as the output layer, holds the prediction value. In our case, since we are trying to find whether a fracture is present or not, the prediction value is contained in a single neuron, and its value after applying a sigmoid function range from 0 to 1, with the predicted class typically being True if the value is greater than 0.5 and False otherwise.



(a) (b)

Figure 1: Architecture of an Artificial Neural Network. (LeCun,2020)

III. RESEARCH METHODOLOGY

Figure 3 below depicts the steps of analysis that would be applied tothe X-ray images stored in the database.

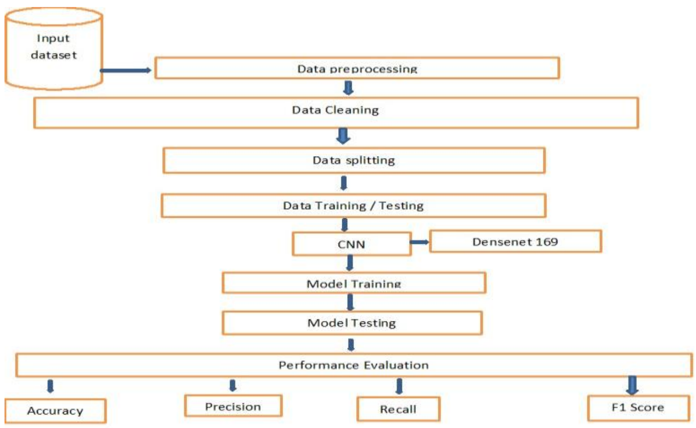


Figure 3: Proposed methodology

A. Data Collection

The Stanford University Medical Centre provided MURA with its dataset. There are sizable dataset of bone X-rays called MURA (musculoskeletal radiographs). Finding out if X-ray scan is abnormal or normal is the job of algorithms. Above 1.7 billion people worldwide suffer from musculoskeletal diseases, which account for 30 million visits to emergency rooms each year and are on the rise. Also, they are common most cause of severe, and chronic impairment. MURA Dataset is the dataset utilized in the research. Hand, Humerus, Shoulder Elbow, Finger, Wrist, and Forearm are just a few of the bones that may be seen in the dataset in X-ray scans. The humerus bone data were the ones taken into account in the current research.

B. Model Detection

The subsequent stage is humerus bone fracture detection, which is carried out using the CNN classifier approach of densenet 169 architecture. These classifiers were primarily chosen because they are quick and easy to use, which speeds up training and improves classification accuracy.

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C. Model Training, Validation and Testing

A training set and a testing set were created from the data set. 30% of the data were used for testing and validation, while the remaining 70% were used for training the model. Using the training dataset and the valid dataset, the suggested Densenet 169 model architecture was tested. Adam served as the optimizer during the training, which involved 12 epochs, a learning rate of 0.0001, a batch size of 32, and the Softmax function.

D. Proposed Model

We proposed employing the DenseNet 169 model to categorize anomalies in the humerus bone seen in X-ray images. The Figure 4 below depicts the DenseNet 169's initial architecture before the change. There are 1000 classes of different things that were classified using the initial DenseNet model. The humerus types of bone defects cannot be directly classified using the original DenseNet 169 model. As a result, we alter it by adding our classifier in place of the top layer. Figure 5 below shows the modified DenseNet 169 model.

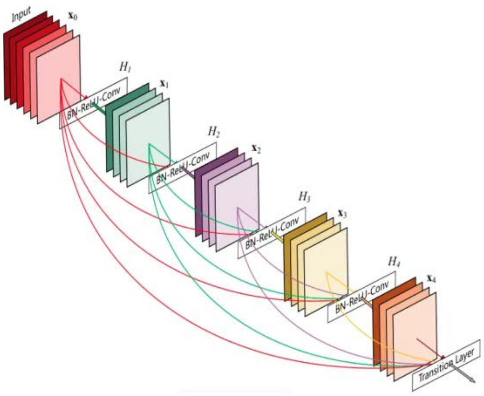

Figure 4: DenseNet 169 architecture (Huang et al., 2018)

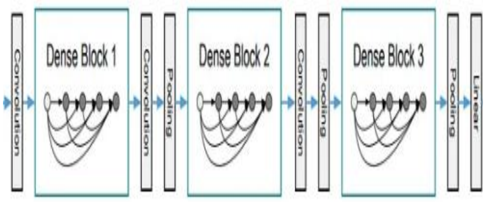

Figure 5: Modified DenseNet 169 architecture

IV. Result and Discussions

a. Method for Conducting the Experiment

The Stanford University Medical Centre provided the data for this research. Images of different bones, including the hand, humerus, shoulder, wrist, elbow, finger, and forearm, can be found in the dataset. Humerus bone data are the ones taken into account in the current investigation. A sizable dataset of bone X-rays is known as MURA (musculoskeletal radiographs). The duty of classifying X-ray images as normal or abnormal is left to algorithms. The process of cleaning the dataset involves removing null values, duplicate data, and noise. After that, it is visualized by being converted from string to numeric numbers. As demonstrated in Figure 6 below, the dataset is imported from Drive into Google Colab.

```
from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive

[ ] %cd '/content/drive/My Drive/MURA-v1.1'

/content/drive/My Drive/MURA-v1.1
```

Figure 6: Import dataset from the drive

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The model for the humerus bone fracture detection system has been built in below Figure 6 utilizing CNN and the Densent 169 architecture.

```
[ ] def build_model():
        base_model = DenseNet169(input_shape=(None, None,3),
                                 weights='imagenet',
                                 include_top=False,
                                 pooling='avg')


        x = base_model.output

        predictions = Dense(n_classes,activation='sigmoid')(x)
        model = Model(inputs=base_model.input, outputs=predictions)
        return model
```

Figure 6: Build model

B. Model Training and Validation and Testing

The training dataset and the valid dataset were both utilized to trained and validated the proposed Densenet 169 model. Using a learning rate of 0.0001, a size of 32 batch, the Softmax function, and Adam acting as the Optimizer, 12 epochs of training were completed. Additionally, augmentation was used to get around any training issues that might come up. Training of the proposed Densenet 169 model's loss and accuracy are displayed in Figure 7 below. We put the Densenet 169 proposed model to the test using the testing dataset after we had finished training it.

```
#train the module
model_history = model.fit(
    train_generator,
    epochs=epochs,
    workers=4,
    use_multiprocessing=False,
    steps_per_epoch = nb_train_samples//batch_size,
    validation_data=validation_generator,
    validation_steps=nb_validation_samples //batch_size,
    callbacks=callbacks_list

)

Epoch 1/12
39/39 [==============================] - 150s 782ms/step - loss: 0.2969 - acc: 0.5968 - mse: 0.2517 - val_loss: 1.0369 - val_acc: 0.6667 - val_mse: 0.2925 - lr: 6
Epoch 2/12
39/39 [==============================] - 21s 523ms/step - loss: 0.1537 - acc: 0.6968 - mse: 0.2147 - val_loss: 0.2593 - val_acc: 0.4444 - val_mse: 0.2751 - lr: 0.
Epoch 3/12
39/39 [==============================] - ETA: 0s - loss: 0.1409 - acc: 0.7411 - mse: 0.1993
Epoch 3: ReduceLROnPlateau reducing learning rate to 0.0001000000474974513.
39/39 [==============================] - 20s 495ms/step - loss: 0.1409 - acc: 0.7411 - mse: 0.1993 - val_loss: 0.3416 - val_acc: 0.6667 - val_mse: 0.2446 - lr: 0.
Epoch 4/12
39/39 [==============================] - 20s 512ms/step - loss: 0.1321 - acc: 0.7573 - mse: 0.1948 - val_loss: 0.1151 - val_acc: 0.7778 - val_mse: 0.1592 - lr: 1.
Epoch 5/12
```

Figure 7: Model Training

e. Training Accuracy Vs. Validation Accuracy

The training accuracy of a model on the data it was trained on is shown in Figure 8 below, whereas the validation accuracy displays the accuracy of a model on new data. This typically demonstrates that training accuracy is higher than validation accuracy.

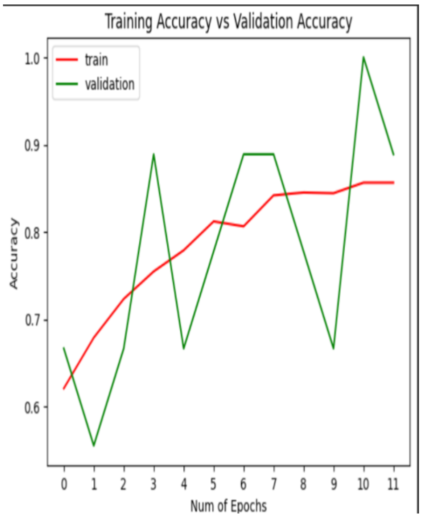

Figure 8: Training accuracy vs. validation accuracy

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V. CONCLUSION

The proposed bone fracture detection system using Densenet 169 has shown promising results in detecting humerus bone fractures in X-ray images. The pre-processing techniques applied, such as segmentation, edge detection, and normalization, have effectively enhanced and highlighted the relevant features in the images. The data augmentation technique was also utilized to increase the dataset size and address the class imbalance problem. The proposed model achieved high accuracy and precision in the classification of bone abnormalities, as well as a high ROC curve measure. The comparison with related studies showed comparable results to radiologists' performance in detecting abnormalities in humerus studies. Overall, this project shows the potential of deep learning models in improving the accuracy and efficiency of fracture diagnosis and treatment.

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CITATION
Mahmoud, A. S., Imam, B. A., Ayagi, S. H., Abubakar, S. B., Mahmud, K., Dansharu, S. R.& Kabir, K. D. (2026). Bone Fracture Detection System Modelusing Deep Learning Techniques for Densenet 169 Architecture. Global Journal of Research in Engineering & Computer Sciences, 6(4), 12–17. https://doi.org/10.5281/zenodo.21282642

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