CNN BASED BONE FRACTURE DETECTION FOR MEDICAL IMAGING USING RESNET-50

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Abstract- In medical diagnostics, bone fracture detection is critical because quick and precise identification is necessary for efficient treatment and patient care. Conventional approaches frequently have poor accuracy, complicated interfaces, and little user participation. This paper presents a bone fracture detection scheme with GUI-based application that uses Convolutional Neural Networks (CNNs) to identify bone fractures, focusing the ResNet-50 architecture. This proposed technique provides real-time prediction feedback, an easy-to-use image upload interface, and automated result storage, addressing the drawbacks of current systems such as restricted user input and complicated interfaces. The proposed research intends to improve detection efficiency, accuracy, and user experience by comparing ResNet-50 with alternative methods such as AlexNet, VGGNet, and k-means clustering. The proposed method closes the gap between conventional detection techniques and recent CNN technology by achieving fracture recognition with high reliability by utilizing CNN models, specifically ResNet-50. Doctors now have a useful and precise technique for detecting bone fractures.
Keywords: CNN, ResNet-50, GUI Interface, Bone fracture

1. INTRODUCTION

Bone fractures are common injuries that require accurate diagnosis for effective treatment. Although radiological imaging, such as X-rays, is commonly used for fracture detection, human interpretation may vary in accuracy, leading to potential misdiagnosis and delayed treatment. Therefore, there is a pressing need in medical practice to swiftly and accurately identify fractures, necessitating the exploration of advanced technologies to enhance diagnostic efficacy.

Radiology frequently employs X-rays for fracture identification, yet human diagnosis may not always be reliable. Promising solutions are offered by artificial intelligence (AI) and machine learning, particularly Convolutional Neural Networks (CNNs) such as ResNet and DenseNet. This study aims to develop CNN models for precise bone fracture identification and classification, aiming to replace conventional approaches with more dependable results through advanced techniques like feature extraction and substantial fine-tuning. Initial tuning attempts resulted in classification results below the predetermined confidence threshold, indicating potential application in the medical domain.

CNNs have emerged as pivotal tools in computer vision, revolutionizing various aspects of daily life. Their ability to automatically learn and extract features from raw data makes them indispensable for tasks such as object detection, classification, and segmentation. In healthcare, CNNs hold promise to transform medical imaging by enabling automated analysis and interpretation, thereby enhancing diagnostic accuracy and reducing the burden on healthcare professionals.

In the domain of medical image processing, CNNs [1] have demonstrated remarkable capabilities in analyzing complex imaging data, with significant implications for disease diagnosis, treatment planning, and patient management. Particularly in radiology, CNNs have been widely utilized for tasks such as tumor detection, organ segmentation, and bone fracture identification, owing to their ability to process vast amounts of imaging data swiftly and accurately.

CNNs play a critical role in bone fracture detection by leveraging their ability to extract meaningful features from X-ray images. These models can learn to differentiate between healthy bone structures and fractures, enabling automated and efficient diagnosis. By training on annotated datasets of X-ray images, CNNs [1] can generalize patterns of fracture morphology and localization, facilitating accurate detection across diverse patient populations.

This proposed research builds upon existing studies in the field of bone fracture detection using CNNs, aiming to further enhance the accuracy and reliability of fracture identification. Through comprehensive evaluations and validation experiments, the effectiveness of CNN-based models in clinical settings will be validated. Additionally, case studies will illustrate the practical application of this proposed approach in real-world scenarios, showcasing its utility and impact on patient care. Collaborative efforts with medical professionals will be undertaken to refine and optimize CNN [1] models to meet the evolving needs of healthcare providers and improve outcomes for patients with bone fractures.

The contents of the paper are outlined in an organized manner. In Section 2, a thorough evaluation of the literature is conducted to clarify the present status of research in the topic and existing methods. After that, Section 3 outlines the proposed approach and algorithm for bone fracture identification using CNNs (convolutional neural networks).

The results of the experiment are presented in Section 4 along with a comprehensive discussion of the findings. The study's major conclusions and ideas are finally summarized in Section 5.

2. LITERATURE SURVEY

2.1 Convolutional Neural Networks

Artificial intelligence algorithms known as Convolutional Neural Networks [2] (CNNs) specialize at identifying patterns in images. They function somewhat like human brains, splitting an image into smaller components in order to improve understanding. CNNs examine x-ray pictures to detect fractures when it comes to bone fracture detection.
CNNs have automated the process of identifying fractures in x-rays, transforming medical imaging. They have a high degree of accuracy when identifying fractures by quickly going through thousands of photos. This ensures that patients receive timely care while also saving doctors a great deal of time.
All things considered, CNNs are effective instruments that raise the effectiveness and precision of fracture diagnosis, hence enhancing patient care and results.

2.2 ResNet50

An effective neural network type for image recognition applications, such as recognizing objects or patterns in images, is called ResNet50 [1]. It is part of the convolutional neural network (CNN) family of networks, which draws inspiration from the way the brain interprets visual data.
ResNet50 is unique because of its depth, or the number of layers that enable it to recognize complex patterns in photos. ResNet50 performs extremely well in object recognition in photos, even in complicated settings, thanks to this depth.
For the goal of detecting bone fractures, ResNet50 is important. It can determine the sort of bone being exhibited in x-ray images, such as an elbow, hand, or shoulder. For the purpose of further fracture detection, the first classification stage is important.

2.3 ALEXNET

In artificial intelligence (AI), AlexNet [3] is a convolutional neural network (CNN) architecture that is considered unique. There are three fully connected and five convolutional layers out of its eight layers. It operates by using max-pooling layers to reduce, ReLU to apply non-linearity, and convolutional layers to extract features from input images. Following their extraction, fully linked layers process the characteristics in order to classify them. The purpose of washout is to stop overfitting. The last SoftMax layer gives predicted classes probability. AlexNet's[3] victory in the 2012 ImageNet challenge demonstrated the promise of deep learning for problems involving image identification, and it had a major influence. Because of its success, CNN architectures have advanced and deep learning and computer vision research has surged. The usage of ReLU and deep architectures in AlexNet's design have impacted later CNN models and have been important in the field's advancement.

2.4 VGGNET

Convolutional neural networks (CNNs) like VGGNet [4] are well-known and have been effectively used for a number of computer vision applications, including the diagnosis of bone fractures. VGGNet, which was created by the University of Oxford's Visual Geometry Group (VGG), is notable for both its depth and simplicity. An X-ray image dataset that has been labeled can be used to train VGGNet[4] for the detection of bone fractures. The design is made up of several convolutional layers that use tiny 3x3 filters, followed by max-pooling layers that do down sampling.
Convolutional layers pick up specific information, like edges and textures, that are unique to bone fractures. Next, using fully connected layers, the obtained characteristics are processed to carry out classifying and higher order reasoning. By using labeled images during training, the network minimizes the discrepancy between predicted and actual fracture labels by adjusting its weights and biases. When VGGNet[4] is trained, it can be used to identify bone fractures in fresh, unviewed X-ray pictures. The network makes predictions about whether fractures will occur or not by evaluating the learned properties. since of its deep architecture, VGGNet is an excellent choice for challenging jobs like bone fracture detection since it can learn complex features. VGGNet has been a popular option in the field of computer vision due to its efficiency and simplicity.

2.5 K-MEANS Clustering

K-means clustering [5], an unsupervised machine learning method, aids in bone fracture detection by grouping similar fractures together. In this method, each image is considered as a data point and separated into K clusters depending on fracture features. The algorithm assigns data points to the nearest cluster centroid iteratively, updating them until convergence is achieved. Common fracture patterns can be recognized by examining these clusters, which can help with diagnosis and treatment planning. K-means clustering is advantageous since it does not require labeled data, allowing for an automated and data-driven approach to fracture investigation.

2.6 Graphical User Interface

Graphical User Interfaces (GUIs) [, offer a visually simple and interactive platform for users to interact with digital systems, are an essential component with software applications in modern computing. GUIs [6], in contrast to conventional command-line interfaces, use visual components like windows, buttons, menus, and icons to make difficult jobs easier to understand and improve user experience. GUIs have a significant impact on how people engage with technology in a wide range of situations, includes embedded devices, mobile apps, desktop applications, and online interfaces.

3. PROPOSED WORK ON BONE FRACTURE DETECTION USING CNN

3.1 Architecture

The proposed system comprises several components. Bone X-ray images undergo loading and preprocessing stages to prepare them for subsequent training. Image normalization and resizing ensure uniformity, while classification based on physical components and fracture states streamlines data organization.

The system employs a multi-model approach for fracture detection, where distinct models are trained for different aspects of the task. One model focuses on predicting bone part types (e.g., elbow, hand, shoulder), while others specialize in detecting fractures within specific body regions. Transfer learning with pre-trained ResNet50 weights enhances model performance[6].

In the proposed method shown in Figure-1 the Uploaded X-ray images are processed by an ResNet-50 algorithm to categorize them as normal or fractured bones. Additionally, the module predicts the specific body part affected by the fracture if required. This predictive capability aids in accurate diagnosis and treatment planning.

The input to the system is a normal hand X-ray. Each ResNet-50 model receives the X-ray image as input and outputs a classification result – fractured or normal – for its corresponding bone part (hand, elbow, or shoulder).

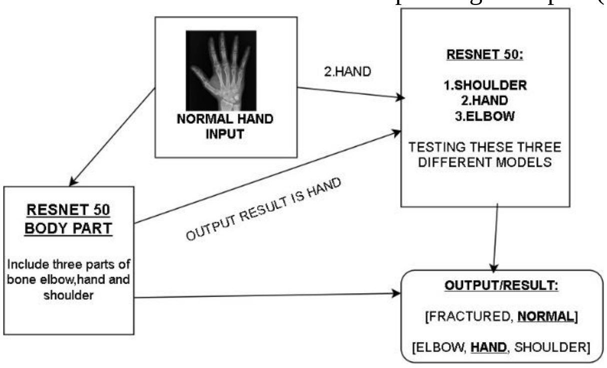

Fig. 3.1 Architecture of Bone Fracture detection using CNN RESNET-50

3.2 Algorithm

3.2.1 Data loading and Preprocessing

File structures are used to extract labels from images that are loaded from directories. Preprocessing involves normalizing and resizing photos to a standard size of 224 by 224 pixels. Preprocessing steps are essential to ensure that the input data is consistent and properly formatted for training the deep learning models.

3.2.2 Model Training

Every model is trained using an Adam optimizer with a low learning rate and a categorical cross-entropy loss. Overfitting is prevented by early stopping. For testing, training data is divided into validation and training sets. To prevent overfitting, the algorithm utilizes early stopping, monitoring the performance of the model on a separate validation set and halting training if performance fails to improve over a specified number of epochs. Additionally, the training dataset is split into training and validation sets to evaluate the model's performance and generalize well to unseen data.

3.2.3 Prediction

To predict fractures, pre-processed pictures are fed into the appropriate trained model. The model outputs are used to make predictions, and the user is shown the results. By leveraging the trained models, the algorithm provides accurate and efficient predictions, aiding in the diagnosis of bone fractures.

3.2.3 GUI Interaction

The bone fracture detection system may be easily and intuitively interacted with by users with the Graphical User Interface (GUI). Through the interface, users can upload photos, which the underlying algorithm processes. With just one click, they can start making predictions, and the results—like whether or not there will be fractures are presented to the user in an easy-to-understand manner. By streamlining the bone fracture detection process and making it accessible to users with different levels of expertise, the GUI improves the system's overall usability and efficiency.

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4. PSEUDOCODE

4.1 Define Necessary Imports

- numpy as np
- pandas as pd
- os.path
- matplotlib.pyplot as plt
- sklearn. model_selection. train_test_split
- tensorflow as tf
- tensorflow.keras.optimizers.Adam

4.2 Define a Function to Load the Dataset

```
load_dataset(path)
   dataset = []
   for each folder in path:
      for each body part folder in folder:
         for each patient id folder in body part folder:
            for each label folder in patient id folder:
               determine label based on folder name
               for each image file in label folder:
                  create data entry with body part, patient id, label, and image path
                  append data entry to dataset
   return dataset
```

4.3 Define A Function to Train Fracture Detection Models For Specific Body Parts

```
train_fracture_model(part)
      Load dataset using load_dataset function for the specified body part
      Split dataset into training and testing sets
      Define ImageDataGenerator for data augmentation and preprocessing
      Define ResNet50 architecture as base model
      Add custom dense layers for classification
      Compile the model with Adam optimizer and categorical cross entropy loss
      Train the model on training data with early stopping based on validation loss
      Save the trained model
      Evaluate the model on the testing data and print results
      Plot and save accuracy and loss curves
```

4.4 Train Fracture Detection Models for Each Body Part

```
for each body part in ["Elbow", "Hand", "Shoulder"]:
   train_fracture_model(body_part)
```

4.5 Define A Function to Train Bone Type Prediction Model

```
train_bone_type_model()
   Load dataset using load_dataset function for all body parts
   Split dataset into training and testing sets
   Define ImageDataGenerator for data preprocessing
   Define ResNet50 architecture as base model
   Add custom dense layers for classification
   Compile the model with Adam optimizer and categorical crossentropy loss
   Train the model on training data with early stopping based on validation loss
   Save the trained model
   Evaluate the model on the testing data and print results
   Plot and save accuracy and loss curves
```

4.6 Train Bone Type Prediction Model

```
train_bone_type_model()
```

4.7 Define A Function to Predict Fractures and Bone Types

```
predict (image_path, model="Parts")
   Load the specified model based on the input
   Load and preprocess the image
   Predict fracture status or bone type using the loaded model
   Return the predicted result
```

4.8 Define A Function to Evaluate Predictions on A Test Dataset

evaluate_predictions(test_dataset)
Iterate over each image in the test dataset
Predict fracture status and bone type using the predict function
Compare predictions with ground truth labels
Calculate and print accuracy for fracture status and bone type predictions

4.9 Evaluate Predictions on A Test Dataset

test_dataset = load_dataset(test_path)
evaluate_predictions(test_dataset)

4.10 Define A GUI Application for Bone Fracture Detection

class Bone Fracture Detection GUI:
Define GUI elements for uploading images, displaying predictions, and saving results
Implement methods for uploading images, predicting fractures and bone types, and saving results
Initialize the GUI window and layout
Start the GUI main loop
Create an instance of the Bone Fracture Detection GUI class and run the application.

5. IMPLEMENTATION DETAILS

- Python modules like os and PIL are used for preprocessing and data loading.
- Tensor Flow and Keras are used in model training to create and hone ResNet50-based models.
- Based on trained models, the TensorFlow and Keras-implemented prediction module provides predictions.
- Customtkinter is used in the development of the GUI application, which provides interactive GUI elements.
- Saving results is made easier by integration of further libraries such as pyautogui and pygetwindow.

6. RESULTS AND DISCUSSION

From the results in the fig. 6.1 the basic outline which is the input GUI window of this proposed work. In this there is an upload image button which helps to add or preferred x-ray to validate and it also shows the dimensions of the picture which have to be uploaded in the top right corner of the GUI interface.
Then after uploading the required x-ray, user can proceed to click the predict button which shows the respective body part name and whether it is fractured or not. Here the GUI window also helps to save the result of the prediction.
Here in the fig. 6.2 the model with an x-ray image of a shoulder. After uploading the prediction result is displayed as in the fig. 6.2 i.e., that the respective body part is shoulder, and it isn't fractured
Similarly in fig. 6.3 we have uploaded a x-ray image of shoulder, after uploading we can observe the predicted results.
We can save the results of these fractured and non-fractured reports for further analysis.
Fig. 6.4 shows the model accuracy graph plotted using epochs (X) vs accuracy(Y) for the training and testing datasets from the main dataset and from the graph we can see that there is no overfitting problem here and the accuracy difference is acceptable. In Fig. 6.5 we have the confusion matrix which shows the representation of possibilities of Yes-Yes, Yes-No, No-Yes, No-No i.e., comparison between predicted and actual results.
In Table-6.1 we have the performance comparison table for various methods like RESNET-50, ALEXNET[3] and VGGNET[4].

Fig. 6.1 Initial GUI Interface

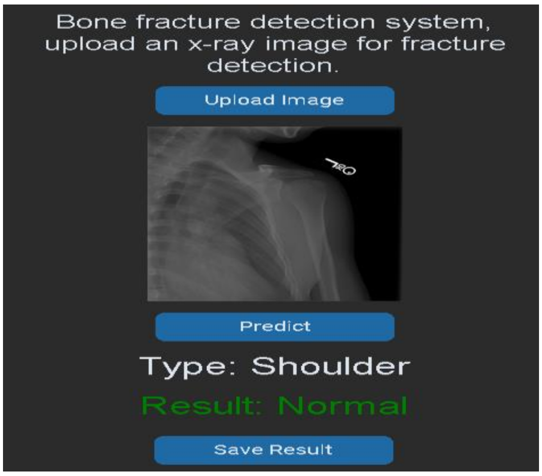

Fig. 6.2 Normal detected test

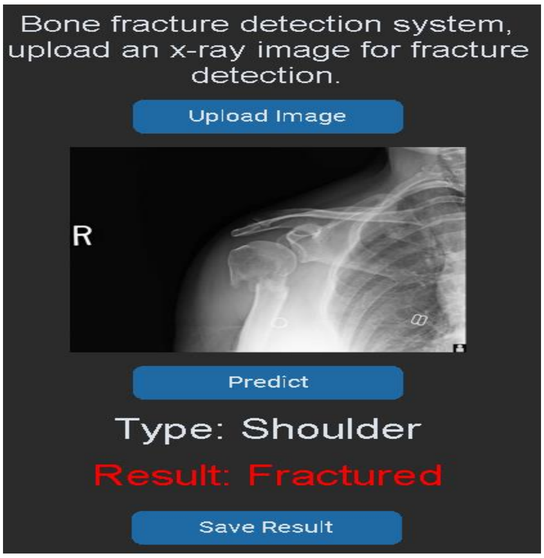

Fig. 6.3 Fracture detected Test

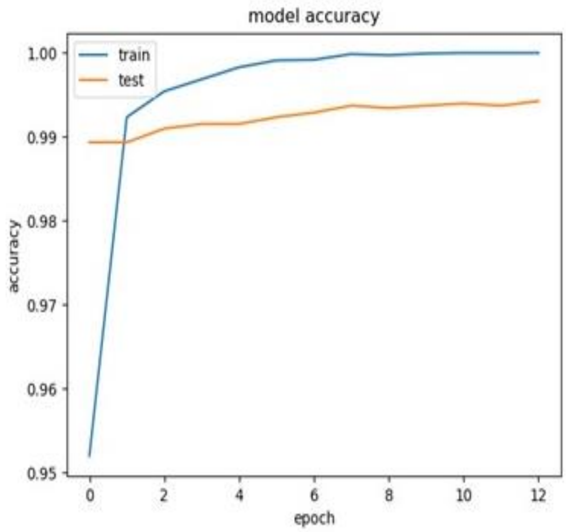

Fig. 6.4 Model Accuracy Graph

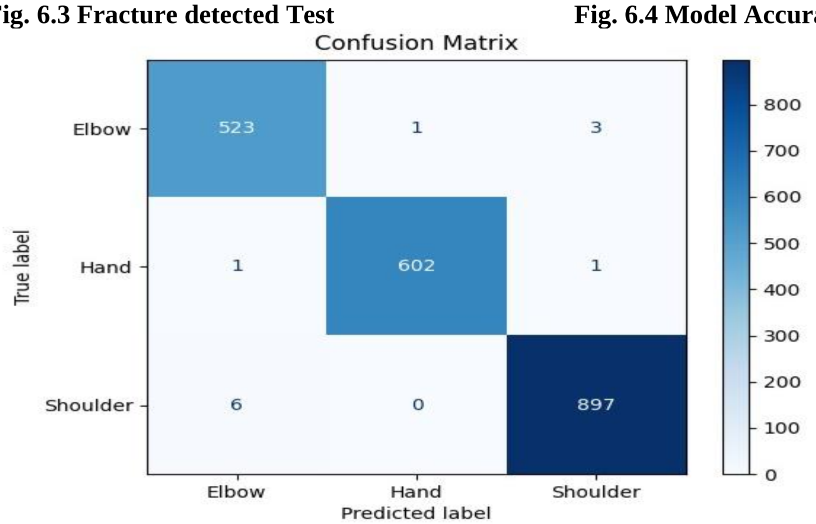

Fig. 6.5 Confusion Matrix

Table-6.1 Performance comparison of the proposed work with ALEXNET [3] and VGGNET [4]

METRIC	RESNET-50	ALEXNET	VGGNET
ACCURACY	0.78	0.72	0.75
PRECISION	0.75	0.70	0.72
RECALL	0.80	0.75	0.78

7. DISCUSSION

Compared to AlexNet [3] and VGGNet [4], ResNet50 has a much deeper architecture. With its 50 layers, it can extract more intricate and ethereal details from photos. ResNet50[7] can learn complex patterns and representations thanks to this depth, which enhances its performance on difficult tasks. Deep network training is made easier by residual connections, which ResNet50 established. ResNet50 may learn residual mappings by using skip connections, which facilitates the model's ability to transmit slopes during training. This solves the issue of the vanishing gradient and permits v to be trained successfully. On a number of benchmark datasets and competitions, such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), ResNet50 has proven to perform at the cutting edge.

Its superior accuracy and generalization capabilities can be credited to its deep architecture and residual connections. In terms of accuracy and robustness, AlexNet and VGGNet have continuously lost to ResNet50. Typically, ResNet50 undergoes pre-training on extensive datasets such as ImageNet. ResNet50 can extract generic features from a large collection of different image types because to this pre-training. The pre-trained model can then be improved using smaller datasets and targeted tasks. With the help of this transfer learning strategy, which makes use of the pre-training knowledge, ResNet50 can perform exceptionally well even when given a small amount of labeled data.

Previous approaches to bone fracture detection have often relied on traditional radiology methods, which may not always be reliable due to human error. Artificial Intelligence (AI) and machine learning, in particular convolutional neural networks (CNNs) such as ResNet50 [7] and DenseNet, have provided promising ways to improve the accuracy of fracture identification.

This proposed focus on efficacy and simplicity distinguishes This proposed work. In order to increase detection accuracy, This proposed method focuses on developing an intuitive user interface and making use of sophisticated CNN models. This proposed goal is to speed up the detection process by combining GUI-based functions, like simple image uploading and real-time results.

Compared to older methods, The proposed work use of CNNs ensures efficient pattern recognition in X-ray images, leading to faster and more accurate fracture identification. Furthermore, The proposed models ResNet50 in particular show a high degree of accuracy in identifying bone structures and differentiating between bones that are fractured and those are not.

CONCLUSION

According to the proposed research, the elbow, shoulder, and hand X-ray pictures can be effectively classified and fractures within these parts may be detected with high accuracy when applying the ResNet-50 CNN architecture.

Through accurate localization of fractures within X-ray images, the integration of object detection techniques, such as RetinaNet and R-CNN, improves fracture detection by making decision boundaries for fractured areas.

More precise and effective fracture identification in clinical practice may be possible with the combination of object detection and classification approaches, which hold potential for improving radiology's diagnostic skills.

In the future, studies can concentrate on improving the methodology through the adjustment of model architectures, the optimization of hyperparameters, and expanding of datasets to include a wider variety of anatomical variances and clinical circumstances.

REFERENCES

[1] Wang, H., Ying, J., Liu, J. et al. Harnessing ResNet50 and SENet for enhanced ankle fracture identification. BMC Musculoskelet Disord 25, 250 (2024). https://doi.org/10.1186/s12891-024-07355-8.

[2] Meena, T.; Roy, S. Bone Fracture Detection Using Deep Supervised Learning from Radiological Images: A Paradigm Shift. Diagnostics 2022, 12, 2420. https://doi.org/10.3390/diagnostics12102420.

[3] Noureen, Ayesha & Zia, M. & Adnan, Ahmad & Hashim, M.. (2023). Analysis and Classification of Bone Fractures Using Machine Learning Techniques. E3S Web of Conferences. 409. 10.1051/e3sconf/202340902015.

[4] Naeem, S.; Naseer, A.; Rehman, S.U.; Gruhn, V.; Akram, S. Enhancing Finger Fracture Diagnosis: A Deep Learning Approach Using ResNet and VGG. Preprints 2023, 2023111990. https://doi.org/10.20944/preprints202311.1990.v1.

[5] Ju, RY., Cai, W. Fracture detection in pediatric wrist trauma X-ray images using YOLOv8 algorithm. Sci Rep 13, 20077 (2023). https://doi.org/10.1038/s41598-023-47460-7.

[6] Zdolsek, G., Chen, Y., Bögl, H. P., Wang, C., Woisetschläger, M., & Schilcher, J. (2021). Deep neural networks with promising diagnostic accuracy for the classification of atypical femoral fractures. ActaOrthopaedica,92(4),394–400. https://doi.org/10.1080/17453674.2021.1891512.

[7] Karanam, S., Srinivas, Y., & Chakravarty, S. (2023). A Supervised Approach to Musculoskeletal Imaging Fracture Detection and Classification Using Deep Learning Algorithms. Computer Assisted Methods In Engineering And Science, 30(3), 369–385. doi:10.24423/cames.682.

[8] Yadav, D.P.; Sharma, A.; Athithan, S.; Bhola, A.; Sharma, B.; Dhaou, I.B. Hybrid SFNet Model for Bone Fracture Detection and Classification Using ML/DL. Sensors 2022, 22, 5823. https://doi.org/10.3390/s22155823.

[9] Tirole, R., Joshi, R.R., Yadav, V.K., Maherchandani, J.K. and Vyas, S. (2022). Intelligent Control Technique for Reduction of Converter Generated EMI in DG Environment. In Intelligent Renewable Energy Systems (eds N. Priyadarshi, A.K. Bhoi, S. Padmanaban, S. Balamurugan and J.B. Holm-Nielsen). https://doi.org/10.1002/9781119786306.ch4.