e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:05/Issue:05/May-2023 Impact Factor- 7.868 www.irjmets.com

BONE FRACTURE DETECTION SYSTEM USING CNN

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DOI : https://www.doi.org/10.56726/IRJMETS39146

ABSTRACT

Bone fractures are common injuries that require accurate and timely diagnosis for proper treatment and management. In this study, we propose a bone fracture detection system based on convolutional neural networks (CNNs) to assist radiologists in the detection and classification of fractures from medical imaging data, such as X-rays. The proposed system aims to automate the fracture detection process and provide an efficient and reliable tool for medical professionals. The CNN-based fracture detection system consists of several key components, including image preprocessing, feature extraction, and classification. In the preprocessing stage, the input X-ray images are preprocessed to enhance image quality and remove noise, ensuring optimal performance during the subsequent stages. Next, the CNN model is utilized to extract meaningful features from the preprocessed images. The model consists of multiple convolutional layers that automatically learn and detect fracture-related patterns and structures. To train the CNN model, a large dataset of labeled X-ray images with fracture annotations is collected and used for model training. The training process involves feeding the images into the network, optimizing the model's parameters using back propagation, and iteratively adjusting the weights to minimize the classification error. The trained model is then evaluated on a separate test dataset to assess its performance in terms of accuracy, sensitivity, specificity, and other relevant metrics.

Keywords: Convolutional Neural Network, Fracture Detection, Fracture Classification, Densest.

I. INTRODUCTION

Missed fractures on emergency department radio graphs are one of the common causes of diagnostic errors and litigation (1). Interpretation errors on radio graphs are contributed by human and environmental factors, such as clinician inexperience, fatigue, distractions, poor viewing conditions, and time pressures. Automated analysis of radio graphs by computers, which are consistent and indefatigable, would be invaluable to augment the work of emergency physicians and radiologists.

In recent years, a machine deep learning technique known as convolution neural networks (CNN's) has gained rapid traction in the field of computer vision. CNN's “learn” discriminating features from the pixel information of large image datasets to fit the diagnostic problem. Continuous improvements of CNN architectures coupled with a geometric increase in hardware computational power have enabled deep learning CNN's to achieve human level performance in lay tasks, such as facial recognition, handwriting recognition, and natural-world image classification (3,4). Early work applying deep learning CNN's to medical diagnostic image analysis has shown promise in areas such as mammography mass classification, pulmonary tuberculosis classification on chest radio graphs, bone age assessment, and diabetic nephropathy classification (5).

A few early studies have shown the feasibility of CNN's in fracture detection on radio graphs (9). Olczak et al (9) achieved an accuracy of 83% for fracture detection using a network trained on a heterogeneous group of hand, wrist, and ankle radio graphs. Kim and MacKinnon (10) were able to attain an area under the receiver operating characteristic curve (AUC) of 0.954 with a model trained on 1389 lateral wrist radio graphs. However, these studies were based on binary classification of entire radio graphs into fracture or non-fracture categories, and these deep learning networks could not localize the actual region of abnormality. It is difficult for clinicians to trust broad classification labels of such “black-box” models, as it is not transparent how the network arrived at its conclusion. Location information of the abnormality is important to support the classification result by providing visual evidence that is verifiable by the clinician.

Object detection CNN's are extensions of image classification models that not only recognize and classify objects on images, but also localize the position of each object by drawing an appropriate bounding box around it (12). Our hypothesis is that an object detection CNN could be used to detect and localize fractures on wrist radio graphs, by treating a fracture as an object. The aim of our study was to determine the feasibility and performance of an object detection CNN to both detect and localize fractures on wrist radio graph

II. METHODOLOGY

A bone fracture detection system using CNN methodology involves the application of Convolutional Neural Networks (CNNs) to analyze medical images, such as X-rays or CT scans, and automatically identify fractures. CNNs are a popular deep learning technique that has shown remarkable performance in various image analysis tasks.

Here is an outline of the steps involved in developing a bone fracture detection system using CNN methodology:

Data collection: Gather a large dataset of medical images containing both normal and fractured bones. These images should be labeled with the corresponding fracture types or categories.

Data preprocessing: Preprocess the collected images to ensure consistency and compatibility for training the CNN model. Common preprocessing steps include resizing the images to a standard size, converting them to grayscale, and normalizing the pixel values.

Data augmentation: To enhance the diversity and generalization ability of the model, apply data augmentation techniques such as rotation, scaling, flipping, and adding noise to artificially expand the training dataset.

Splitting the dataset: Divide the dataset into training, validation, and testing subsets. The training set is used to train the CNN model, the validation set helps in monitoring the model's performance during training and tuning hyperparameters, and the testing set evaluates the final model's performance.

Model architecture design: Design the CNN architecture for bone fracture detection. Typically, a CNN consists of multiple convolutional layers, pooling layers for downsampling, and fully connected layers for classification. You can experiment with different architectures, such as variations of VGGNet, ResNet, or InceptionNet, and customize them according to your requirements.

Model training: Train the CNN model using the training dataset. During training, the model learns to extract relevant features from the input images and make predictions. The weights of the CNN are updated iteratively using optimization algorithms such as stochastic gradient descent (SGD) or Adam.

Hyperparameter tuning: Experiment with different hyperparameter settings, such as learning rate, batch size, number of layers, and filter sizes, to optimize the performance of the CNN model. This can be done by monitoring the model's performance on the validation set.

Model evaluation: Evaluate the trained CNN model using the testing dataset. Measure performance metrics such as accuracy, precision, recall, and F1-score to assess how well the model can detect fractures.

Deployment: Once the model has been trained and evaluated, deploy it in a production environment, where it can be used to automatically detect bone fractures in new, unseen images.

It's important to note that developing a bone fracture detection system using CNN methodology requires a significant amount of labeled data, computational resources, and expertise in deep learning and medical imaging. Additionally, it's crucial to collaborate with medical professionals to ensure the accuracy and reliability of the system in real-world scenarios.,

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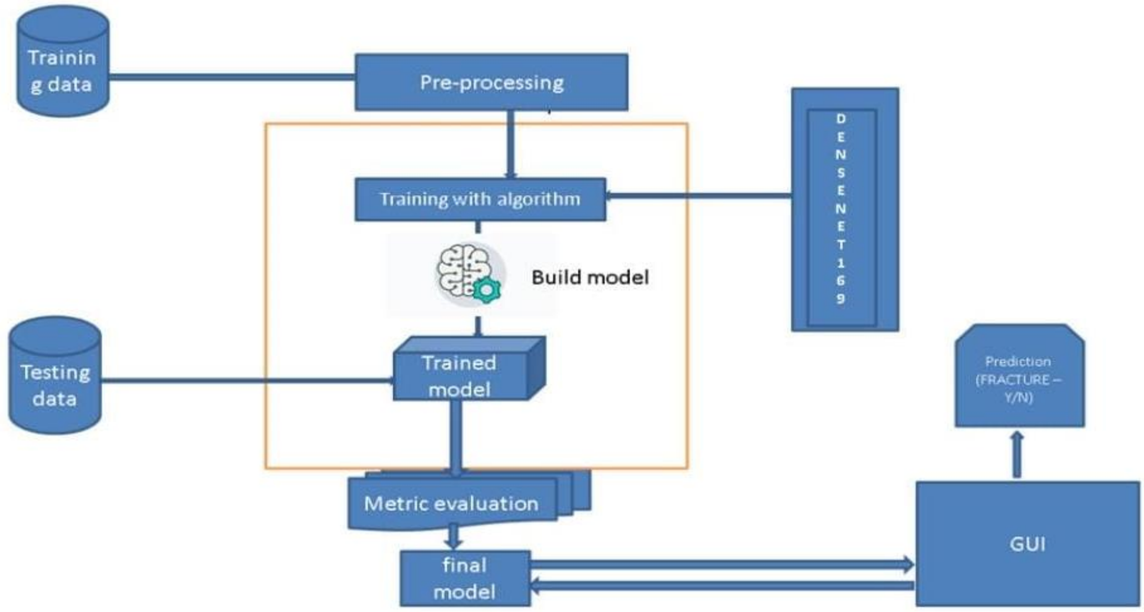
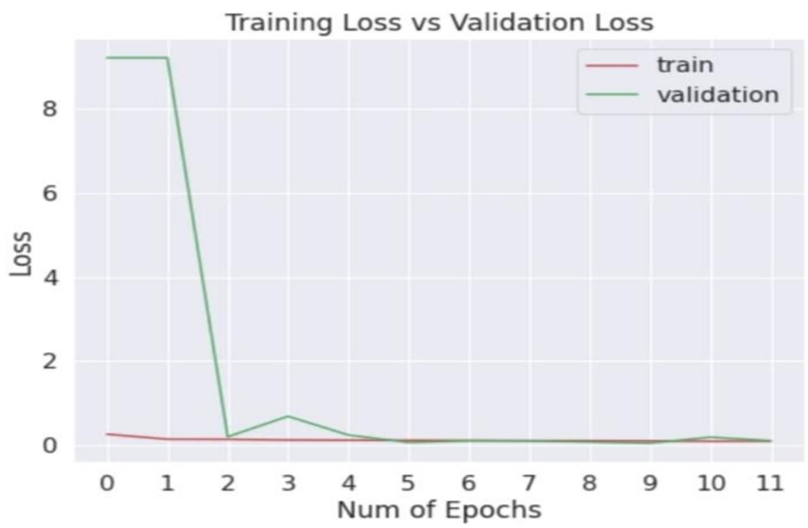
III. MODELING AND ANALYSIS



IV. RESULTS AND DISCUSSION

The use of a computer-based system to detect the specific location of fractures in bones through X-ray has the potential to improve the accuracy and efficiency of fracture detection. The use of a convolutional neural network (CNN) algorithm in this study can improve the accuracy of the system compared to other existing methodologies, as it can perform multi-resolution analysis and identify minor details during the analysis period. This means that the system can potentially detect fractures that may have been missed by other methods. The use of the CNN algorithm in this study may lead to improved accuracy in the detection of fractures in bones. By performing multi-resolution analysis, the algorithm can potentially identify minor details that may have been missed by other methods, which can improve the overall accuracy of the system. The specific results of the study would depend on the datasets used and the performance of the algorithm in detecting fractures. The use of a computer-based system with a CNN algorithm for fracture detection in bones is a promising development in the field of medical imaging. By incorporating multi-resolution analysis, the algorithm can potentially detect fractures that may have been missed by other methods, which can improve the accuracy and reliability of fracture detection. However, further studies are needed to determine the specific performance of the algorithm in detecting fractures, and to validate the results of the study. Additionally, the development of computer-based systems for fracture detection could potentially lead to improved patient outcomes, by allowing for earlier detection and treatment of fractures.



V. CONCLUSION

A bone fracture detection system using Convolutional Neural Networks (CNNs) has the potential to greatly enhance medical diagnosis and treatment planning. CNNs have proven to be highly effective in image recognition tasks, including medical imaging analysis. By training a CNN model on a large datasets of bone fracture images, it can learn to accurately detect and classify fractures, helping physicians make more informed decisions. The advantages of using a CNN-based bone fracture detection system are numerous. First and foremost, it can improve the accuracy and speed of fracture detection, enabling earlier diagnoses and treatments. This can be critical in emergency situations or when dealing with complex fractures that require immediate attention. Additionally, the system can assist radiologists and other healthcare professionals by reducing their workload and providing a second opinion. Furthermore, a CNN-based system can help standardize fracture diagnosis by reducing subjective interpretation and variability among different practitioners. The model can be trained on a diverse range of fracture patterns, allowing it to recognize even rare or uncommon fractures accurately. This can lead to improved patient outcomes and a more efficient healthcare system. However, it is important to acknowledge that a bone fracture detection system based on CNNs is not without limitations. The performance of the model heavily relies on the quality and diversity of the training data. Access to large annotated datasets is essential for training an accurate and robust model. Additionally, the system's performance may be affected by factors such as image quality, patient demographics, and the presence of other abnormalities or pathologies. Moreover, the deployment of such a system requires careful consideration of ethical and legal aspects, including patient privacy, data security, and the responsibility of healthcare professionals in interpreting the model's output. The system should be seen as a valuable tool to support clinical decision-making rather than a replacement for human expertise. a bone fracture detection system using CNNs holds great promise for improving fracture diagnosis and treatment. With further advancements in training methodologies, data collection, and model refinement, it has the potential to become an invaluable tool in the field of radiology, ultimately benefiting patients and healthcare providers alike

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