Classification of Bone Abnormalities in MURA

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MURA 에서 골 이상 분류 알고리즘

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Abstract

Musculoskeletal abnormalities pose a significant diagnostic challenge in medical imaging, necessitating accurate and efficient detection methods. In this study, we address the challenges associated with such abnormalities by developing a deep learning-based approach for abnormality detection in musculoskeletal radiographs. Leveraging the rich representation learning capabilities of a 169-layer Densenet model, we propose a solution that combines transfer learning and fine-tuning to the task at hand. Furthermore, extensive data augmentation techniques are employed to enhance the model's generalization capability and robustness to diverse imaging conditions. Our proposed approach achieves state-of-the-art performance in abnormality detection. The results demonstrate the effectiveness of the model in aiding the clinical decision-making of radiologists and improving diagnostic accuracy. Overall, our study highlights the efficacy of deep learning-based approaches in classifying abnormalities in radiographic images.

Ⅰ. Introduction

MURA is a large dataset [1] of Musculoskeletal radiographs containing 40,561 images from 14,863 studies and 12,251 patients, and each study is labelled manually by radiologists to be either normal or abnormal. Misdiagnosing after X-ray, CT or other radiographs is the main problem that is directly connected to the radiologist factor because of the huge workload due to a high number of patients which in turn shorten the time that specialists must evaluate the radiographs. These mistakes have serious consequences which often result in delayed treatment, risk of fracture in the future, increase treatment and even disability of patients in the long term. Musculoskeletal traumas affect more than 1.7 billion people a year [2] [3]. It requires expert diagnosis of such abnormalities [4]. Traditional approaches often rely on manual assessment of bone X-rays which is time-consuming [5]. To address these limitations, a deep learning model is proposed to detect abnormalities in musculoskeletal radiographs. We train a 169-layer DenseNet [6] model to detect and localize abnormalities. We contribute by fine-tuning the model through transfer learning[7], thereby enhancing its adaptability to the specific domain. Furthermore, extensive data augmentation techniques are applied to enrich datasets and improve model robustness.

Ⅱ. Proposed Methodology

We begin by acquiring the MURA dataset from Stanford official comprising diverse range of radiographs, ensuring it encompasses a diverse range of abnormalities. Thus, we first preprocess the dataset to extract the region of interest (ROI) and enhance the quality of the images. We trained different pre-trained models and then picked the model with the best accuracy. For the main model we leverage DenseNet169, which strikes a good balance between complexity and efficiency. Initially, the model is loaded with its learned weights from the previous session, this step initializes the model with valuable features of the image. Then the features from layers preceding the classification layers are extracted, which is responsible for capturing high-level abstract features from input images. To serve the purposes of classification, a new layer is added on top of base model.

To adapt the model to our specific tasks, the model undergoes fine-tuning, in which the weights of both pre-trained layers and the new classification layers are updated. After training the model is optimized and evaluated using validation data to ensure its effectiveness in classifying abnormalities, this step helps in fine-tuning the hyperparameters and assessing the model performance. The model architecture is illustrated in Figure 1.

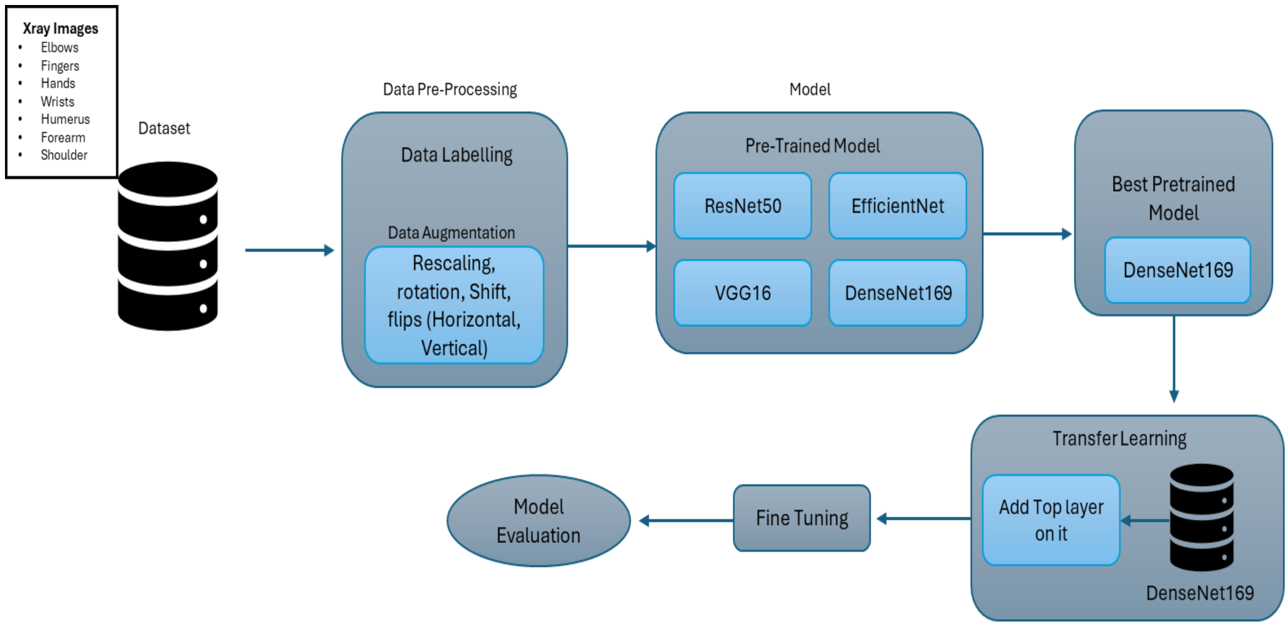

Figure 1 Overall Architecture of the Model

Ⅲ. Experimental Results

The trained dataset was evaluated on the MURA dataset.. The model performance was measured using accuracy and loss function. The model is trained for 10 epochs on benchmarks followed by another 10 epochs after applying transfer learning and fine tuning. The results demonstrate that the proposed model achieved better results. The results are illustrated in table 1 and Fig 2.

Table 1 Quantitative Results

Methods	Accuracy	Loss
ResNet50 [8]	64.32	0.66
EfficientNetB0 [9]	65.42	0.60
VGG16 [10]	69.73	0.55
DenseNet169 [6]	74.86	0.51
Ours	**81.16**	**0.43**

IV. Conclusion

To conclude, our work showcases the efficiency of DenseNet augmented with transfer learning and fine-tuning for abnormalities detection in MURA. Through extensive experiments, we have developed a robust system that accurately identifies abnormalities in skin radiographs. Our results demonstrate the effectiveness of our proposed methodology, with the model achieving the highest performance in finger and wrist images.

ACKNOWLEDGMENT

This research was supported by "Regional Innovation Strategy (RIS)" through the National Research Foundation of Korea (NRF) funded by the Ministry of Education(MOE) (2021RIS-002) and funded by the Korea government (MSIT) (No. RS-2023-00217471).

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