Fracture Detection in Musculoskeletal Radiographs

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***Abstract*—This document is a report on the third milestone of the Data Science in Medical project. In this part, there are new methods of detecting fractures proposed, using the same dataset as in the previous milestone, MURA v1.1 [5]. There were conducted extensive experiments to assess the difference in model choice, fine-tuning the models, and augmentating the data. The project implemented a hybrid approach for fracture detection, leveraging DCGAN for data augmentation and EfficientNet-B0 for classification, used with Bayesian optimized parameters.**

***Index Terms*—Fracture Detection, Generative Adversarial Networks, EfficientNet, Hyperparameter Tuning, Bayesian Optimization.**

I. Introduction

For this milestone, a novel approach is proposed, but also an improvement on the old project is done. From conducted research, there is a lack of documented use of DCGAN and EfficientNet together, although existing studies and implementations that contain these solutions independently of each other [1], [2].

II. Argumentation

A. EfficientNet

EfficientNet is a family of convolutional neural networks (CNNs) designed to achieve high performance on image classification tasks while being computationally efficient [3]. It was introduced by Google AI in 2019 and is based on the principles of model scaling, where the width, depth, and resolution of a network are scaled in a balanced manner to optimize accuracy and efficiency [4]. EfficientNet achieves higher accuracy with fewer parameters and FLOPs compared to traditional architectures such as ResNet, used in the previous milestone [5]. It is well-suited for various computer vision tasks, including image classification [6].
EfficientNet's computational efficiency and accuracy made it an ideal candidate for our task. In this project, EfficientNet-B0, the base model, was utilized, for fracture detection.

B. DCGAN

Deep Convolutional Generative Adversarial Networks (DCGAN) represent an architecture for generative tasks, combining the power of convolutional neural networks (CNNs) with the adversarial training framework [7].
By generating realistic synthetic radiographic images, DCGAN effectively augments the dataset, increasing its size and diversity. This helps the model learn features that might be underrepresented in the original data, reducing overfitting and improving robustness.
Moreover, DCGAN offers a cost-efficient alternative to collecting and annotating new medical images [8].
By combining real and synthetic data, DCGAN significantly contributes to the robustness and reliability of the fracture detection system.

C. Bayesian Optimization

Bayesian Optimization is a probabilistic technique for hyperparameter tuning that builds a surrogate model to predict the performance of different configurations and iteratively refines its search to find the best parameters efficiently [9], [10].
In this project, it was helpful in optimizing the hyperparameters of the EfficientNet-B0 model for bone fracture detection. Key parameters, such as the learning rate, were fine-tuned by balancing exploration of the search space by exploiting promising configurations.
This approach demonstrated the importance of efficient hyperparameter tuning in achieving good results.

III. Pipeline

A. Dataset Preparation

The project utilized the MURA dataset, a large collection of musculoskeletal radiographs labeled for abnormalities. The data preparation involved:
Label Mapping: Labels were extracted from directory names in the dataset, ensuring accurate association between image paths and their corresponding labels.
DCGAN for Synthetic Data Generation: A DCGAN was employed to generate synthetic radiographic images of fractured and non-fractured bones. The DCGAN comprises:

- Generator: Learns to create realistic images from random noise.
- Discriminator: Distinguishes between real and generated images, iteratively improving the generator's outputs.

Fig. 1. DCGAN Generator

Fig. 2. DCGAN Discriminator

After 25 epochs of training on the MURA dataset, the generator produced 15,000 synthetic images. These images were visually validated and added to the training dataset. The augmented dataset significantly improved the diversity of fracture cases.
Data Augmentation: To enhance model generalization, augmentations such as resizing, cropping, flipping, brightness adjustment, and Gaussian blur were applied using the Albumentations library.
Splitting Strategy: The dataset was split into training, validation, and test sets with an 80-20 train-validation ratio. An additional augmented dataset was concatenated with the original training set to improve model robustness.

B. Model Architecture

The backbone of the system is EfficientNet-B0, pre-trained on ImageNet. Key modifications include:

- Replacing the classifier head to predict two classes (fractured or non-fractured).
- Applying transfer learning by fine-tuning the pre-trained weights.

C. Training Process

The model was trained for 25 epochs with a batch size of 64 using the Adam optimizer and a learning rate of 0.001. The loss function was cross-entropy, suitable for binary classification tasks.

D. Bayesian Optimization

To optimize model hyperparameters, Bayesian Optimization was applied to find the best learning rate and beta1 parameter for the Adam optimizer.
Search Space: lr: Continuous range from 1e-4 to 1e-2, beta1: Continuous range from 0.5 to 0.9.
Optimal Parameters The optimization yielded the best values: Learning Rate: 0.0015, beta1: 0.85
The model was retrained with these optimized parameters, significantly improving performance.

E. Evaluation

The trained model was evaluated on a separate test set using accuracy, f1-score. ROC-AUC, confusion matrix.

IV. Results and Visualizations

After 25 epochs using DCGAN, 15000 new images were obtained:

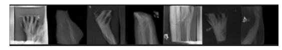

Fig. 3. Generated images usin DCGAN

Final results:

- Test Accuracy: 0.7545%
- Test F1-Score: 0.7294%
- Test ROC-AUC: 0.819%

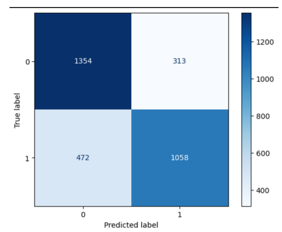

Fig. 4. Confussion Matrix

Improvements Over Previous Results

In the earlier implementation using ResNet50 without data augmentation, the performance metrics achieved were as follows [5]:

- Test Accuracy: 73.35%
- Test F1-Score: 70.48%
- Test ROC-AUC: 79.74%

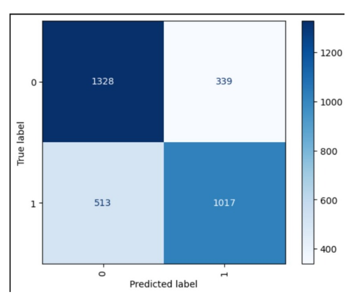

Fig. 5. Confusion Matrix of Resnet50 without Data Augmentation

When experimenting with training, we also tried a simple EfficientNet without DCGAN and hyperarameter tuning and these were the results:

- Test Accuracy: 80.67%,
- Test F1-Score: 78.59%,
- Test ROC-AUC: 86.68%.

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