Università di Pisa

Computational Intelligence and Deep Learning

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Contents

Chapter 1

Introduction

Breast cancer is one of the most common types of cancer in women. Early detection and treatment can effectively improve cure rates and reduce mortality. Detecting breast cancer using mammographic images is a cost-effective technique, and radiologists can make a diagnosis by analyzing these images. However, the large number of mammographic images produced day by day has brought a huge workload on radiologists and also increased the rate of misdiagnosis. Therefore, developing a computer-aided diagnosis (CAD) system can significantly relieve the pressure on radiologists and improve the diagnosis accuracy.

Machine learning therefore quickly enters the picture, based on large, heterogeneous data sets, the automatic analysis for mammography images needs to be analyzed and make predictions from the regions of interest and classify these regions into normal or abnormal (benign and malignant).

1.1 Notebooks

1. **Knowing the Dataset**
    - Knowing_DDSM_dataset.ipynb
2. **CNN from Scratch**
    - Scratch_CNN_benign_vs_malign.ipynb
    - Scratch_CNN_masses_vs_calc.ipynb
3. **PreTrained**
    - PreTrained_CNN_benign_vs_malign.ipynb
    - PreTrained_CNN_masses_vs_calc.ipynb
4. **Baseline**
    - BaselineCNN.ipynb
5. **Esemble**
    - Ensemble.ipynb

Chapter 2

Convolutional Neural Network for Medical Imaging Analysis

On this investigation, the main objective is to perform abnormality classification in mammography using Convolutional Neural Networks for Medical Imaging Analysis. This laboratory research will be development with a standart evaluation data set in the area of decision support systems in mammography, the *Digital Curated Breast Imaging Subset of Database for Screening Mammography* **(CBIS DDSM)**

2.1 Original Dataset

The dataset we will focus on is an updated and standardized version of the Digital Database for Screening Mammography (DDSM). The DDSM is a database of 2,620 scanned film mammography studies. It contains normal, benign, and malignant cases with verified pathology information. Few well-curated public datasets have been provided for the mammography community. These include the DDSM, the Mammographic Imaging Analysis Society (MIAS) database, and the Image Retrieval in Medical Applications (IRMA) project. Although these public data sets are useful, they are limited in terms of data set size and accessibility.

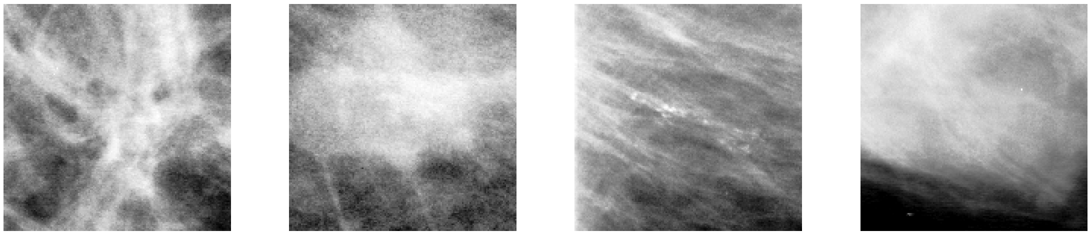
> Lee, Rebecca Sawyer, et al. *'A curated mammography data set for use in computer-aided detection and diagnosis research'* Scientific data 4 (2017): 170177.

The images have been decompressed and converted to DICOM format. Updated ROI segmentation and bounding boxes, and pathologic diagnosis for training data are also included. The data set contains 753 calcification cases and 891 mass cases, providing a data-set size capable of analyzing decision support systems in mammography.

In the subsequent sections, data source, data preprocessing, data augmentation, model development and evaluation will be delineated. A simple example of the image provided from the original dataset:

Design Types	-Design Types and Parallel group design. -Feature extraction objective. -Image processing objective
Measurement Type	Mammography
Technology Type	Digital curation
Factor Type	Diagnosis
Sample Characteristic	Homo sapiens

Table 2.1: DDSM Data Set description.



(a) Mass, Benign

(b) Mass, Malignant

(c) Calcification, Benign

(d) Calcification, Malignant

Figure 2.1: Medical Image Representation

Considering the benefits of using deep learning in image classification problem (e.g., automatic feature extraction from raw data), develop a deep Convolutional Neural Network (CNN) that will be trained to read mammography images and classify them into the following five instances:

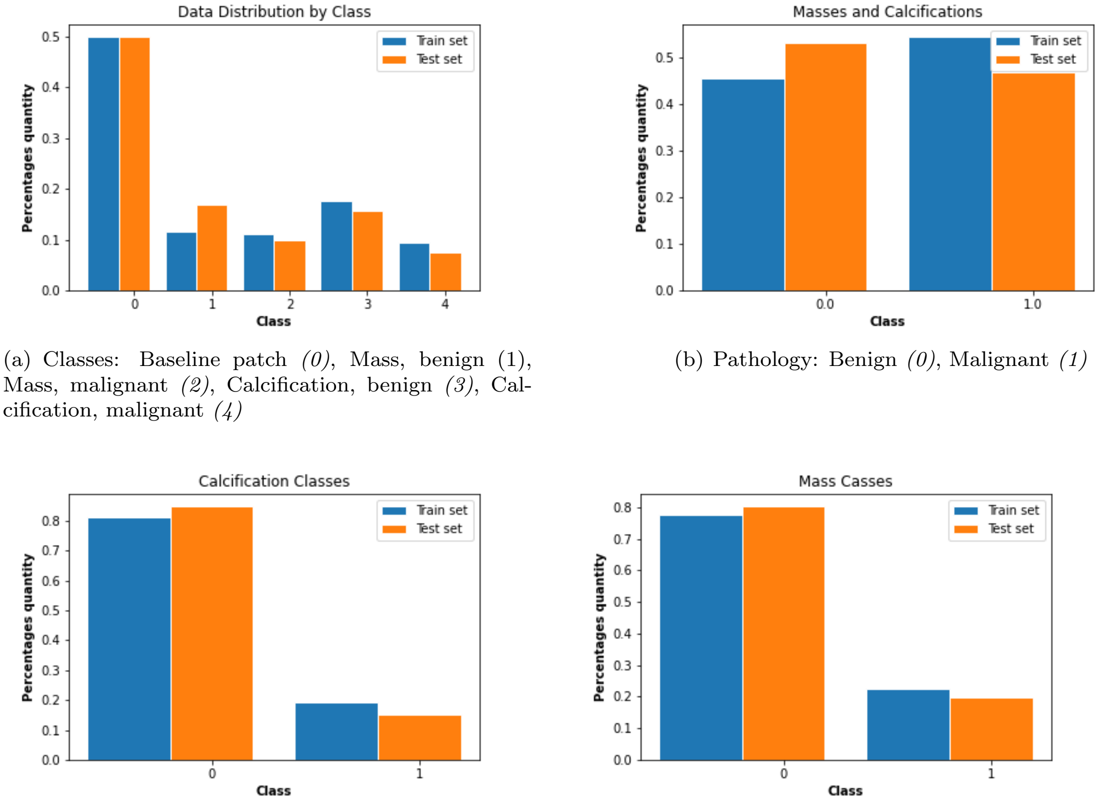
- Normal
- Benign Calcification
- Benign Mass
- Malignant Calcification
- Malignant Mass

2.2 Data Records

The images are distributed at the full mammography and abnormality level as DICOM files. Full mammography images include both MLO and CC views of the mammograms. Abnormalities are represented as binary mask images of the same size as their associated mammograms.

As we mention previously, *CBIS DDSM:* Curated Breast Imaging Subset of Digital Database for Screening Mammography.

A description of the dataset is provided in:



(a) Classes: Baseline patch *(0)*, Mass, benign (1), Mass, malignant *(2)*, Calcification, benign *(3)*, Calcification, malignant *(4)*

(b) Pathology: Benign *(0)*, Malignant *(1)*

(c) Pathology: Benign *(0)*, Malignant *(1)*

(d) Pathology: Benign *(0)*, Malignant *(1)*

Figure 2.2: Data Representation

Chapter 3

CNN from Scratch with Python

3.1 Masses and Calcifications

3.1.1 Data Preparation

- Data Loading
- Data Reshape
- Data Normalization
- Splitting into Training and Validation data

This can be easily done with the Python data manipulation. Modern deep learning provides a very powerful framework for supervised learning, we introduce on this step the convolutional network for scaling to large images.

3.1.2 Building CNN Architecture

- Definition CNN Model
- Data Optimizer

Test Num	Batch size	Epochs	Optimizer	Loss	Accuracy	Precision	Recall	AUC
1	20	100	RMSprop	0.7444	0.8313	0.8519	0.7718	0.8803
2	20	100	Adam	0.8893	0.8031	0.7829	0.7987	0.8761
3	20	100	Nadam	0.7338	0.8156	0.7885	0.8255	0.9022

Table 3.1: Comparation Optimizer

3.1.3 Visualization of the Data

3.1.4 Fighting Overfitting

- CNN Model No.1 Data Augmentation
- CNN Model No.2 K-fold cross validation

3.1.5 Hyperparameter Tuning

We create a sort of experimental results, creating a manual tuning between the values: Optimizer (Adam and RMSprop) and Learning Rate (0.01, 0.001, 0.0001), Changing Batch size (20, 32, 64, 128).

Our goal is to select the smallest loss model with good enough accuracy.

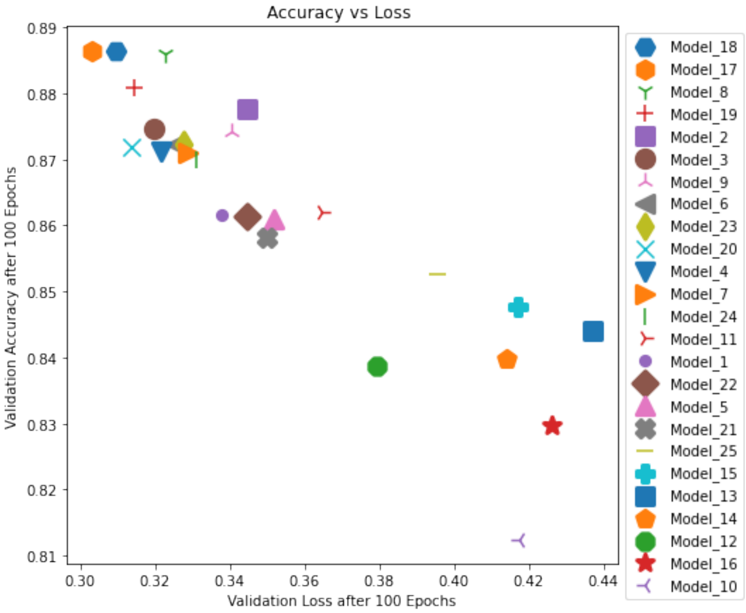


Figure 3.1: Results of Model Accuracy vs. Model Loss

3.1.6 Testing the best 3 models

3.1.7 Choose the best model

3.2 Benign and Malignant

batch size	num epochs	units per layer	optimizer	learning rate	mean val acc	mean val loss	num folds
20	100	[32 64 128 128]	RMSprop	0.01	0.8615	0.3377	5
20	100	[32 64 128 256]	RMSprop	0.01	0.8777	0.3445	5
20	100	[32 64 128 128]	Adam	0.01	0.8746	0.3198	5
20	100	[32 64 128 256]	Adam	0.01	0.8712	0.3218	5
20	100	[32 64 128 128]	RMSprop	0.001	0.8865	0.3032	5
20	100	[32 64 128 256]	RMSprop	0.001	0.8865	0.3096	5
20	100	[32 64 128 128]	Adam	0.001	0.8808	0.3143	5
20	100	[32 64 128 256]	Adam	0.001	0.8719	0.3136	5
20	100	[32 64 128 128]	RMSprop	0.0001	0.8796	0.3183	5
20	100	[32 64 128 256]	RMSprop	0.0001	0.8704	0.3300	5
20	100	[32 64 128 128]	Adam	0.0001	0.8815	0.3031	5
20	100	[32 64 128 256]	Adam	0.0001	0.8554	0.3688	5

Table 3.2: Results using the batch size: 20

batch size	num epochs	units per layer	optimizer	learning rate	mean val acc	mean val loss	num folds
32	100	[32 64 128 128]	RMSprop	0.01	0.8609	0.3520	5
32	100	[32 64 128 256]	RMSprop	0.01	0.8723	0.3259	5
32	100	[32 64 128 128]	Adam	0.01	0.8711	0.3289	5
32	100	[32 64 128 256]	Adam	0.01	0.8859	0.3226	5
32	100	[32 64 128 128]	RMSprop	0.001	0.8582	0.3498	5
32	100	[32 64 128 256]	RMSprop	0.001	0.8613	0.3446	5
32	100	[32 64 128 128]	Adam	0.001	0.8723	0.3278	5
32	100	[32 64 128 256]	Adam	0.001	0.8699	0.3309	5
32	100	[32 64 128 128]	RMSprop	0.0001	0.8727	0.3319	5
32	100	[32 64 128 256]	RMSprop	0.0001	0.8664	0.3441	5
32	100	[32 64 128 128]	Adam	0.0001	0.8688	0.3460	5
32	100	[32 64 128 256]	Adam	0.0001	0.8730	0.3359	5

Table 3.3: Results using the batch size: 32

batch size	num epochs	units per layer	optimizer	learning rate	mean val acc	mean val loss	num folds
64	100	[32 64 128 128]	RMSprop	0.01	0.8742	0.3405	5
64	100	[32 64 128 256]	RMSprop	0.01	0.8125	0.4174	5
64	100	[32 64 128 128]	Adam	0.01	0.8621	0.3646	5
64	100	[32 64 128 256]	Adam	0.01	0.8387	0.3795	5
64	100	[32 64 128 128]	RMSprop	0.001	0.8527	0.3954	5
64	100	[32 64 128 256]	RMSprop	0.001	0.8684	0.3482	5
64	100	[32 64 128 128]	Adam	0.001	0.8414	0.3946	5
64	100	[32 64 128 256]	Adam	0.001	0.7875	0.4502	5
64	100	[32 64 128 128]	RMSprop	0.0001	0.8613	0.3523	5
64	100	[32 64 128 256]	RMSprop	0.0001	0.8562	0.3706	5
64	100	[32 64 128 128]	Adam	0.0001	0.8109	0.4174	5
64	100	[32 64 128 256]	Adam	0.0001	0.8363	0.4063	5

Table 3.4: Results using the batch size: 64

batch size	num epochs	units per layer	optimizer	learning rate	mean val acc	mean val loss	num folds
128	100	[32 64 128 128]	RMSprop	0.01	0.8441	0.4371	5
128	100	[32 64 128 256]	RMSprop	0.01	0.8398	0.4141	5
128	100	[32 64 128 128]	Adam	0.01	0.8477	0.4169	5
128	100	[32 64 128 256]	Adam	0.01	0.8297	0.4262	5
128	100	[32 64 128 128]	RMSprop	0.001	0.7937	0.5057	5
128	100	[32 64 128 256]	RMSprop	0.001	0.8520	0.4182	5
128	100	[32 64 128 128]	Adam	0.001	0.7594	0.4973	5
128	100	[32 64 128 256]	Adam	0.001	0.8152	0.4529	5
128	100	[32 64 128 128]	RMSprop	0.0001	0.8301	0.4478	5
128	100	[32 64 128 256]	RMSprop	0.0001	0.8195	0.4629	5
128	100	[32 64 128 128]	Adam	0.0001	0.8316	0.4299	5
128	100	[32 64 128 256]	Adam	0.0001	0.8316	0.4338	5

Table 3.5: Results using the batch size: 128

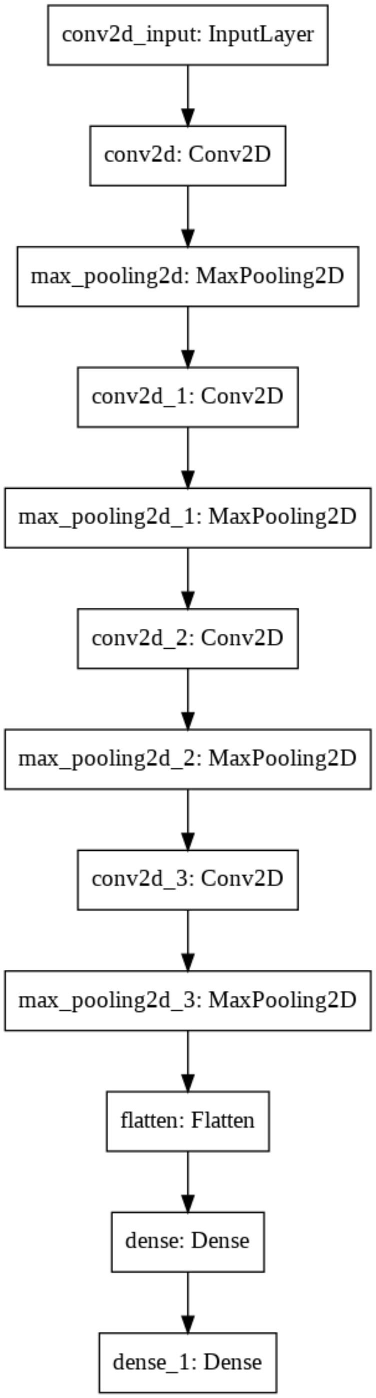

conv2d_input: InputLayer
conv2d: Conv2D
max_pooling2d: MaxPooling2D
conv2d_1: Conv2D
max_pooling2d_1: MaxPooling2D
conv2d_2: Conv2D
max_pooling2d_2: MaxPooling2D
conv2d_3: Conv2D
max_pooling2d_3: MaxPooling2D
flatten: Flatten
dense: Dense
dense_1: Dense

Figure 3.2:

Chapter 4

Pre-Trained CNN

Chapter 5

Baseline Abnormality detection in mammography

Chapter 6

Ensemble of Neural Networks

6.1 Examples of Predictions