Università di Catania

Prothesis Joint Infection detection

Academic year 2023-2024

Giovanni Spadaro, Gabriele Tuccio

Mar 1, 2024

Contents

List of Figures

List of Tables

Chapter 1

Introduction and data preprocessing

1.1 Introduction

Medical imaging is a pivotal field within healthcare, revolutionizing diagnostics and treatment planning by providing non-invasive visualizations of the body's internal structures. Utilizing various technologies such as X-rays, ultrasound, MRI (Magnetic Resonance Imaging), CT (Computed Tomography), and nuclear medicine, medical imaging enables clinicians to accurately detect, diagnose, and monitor a wide array of diseases and conditions.

Each imaging modality offers distinct advantages and is suited to different clinical scenarios. X-rays excel in bone imaging, while ultrasound is ideal for soft tissue examination and real-time imaging during procedures. MRI and CT provide detailed anatomical images for assessing organs and soft tissues with differing levels of contrast and spatial resolution. Nuclear medicine techniques, including PET (Positron Emission Tomography), facilitate functional imaging by tracking molecular processes within the body.

Moreover, advancements in medical imaging are continually enhancing diagnostic accuracy and patient outcomes. Integration with artificial intelligence and data science further augments the field by enabling automated analysis, quantitative measurements, and personalized medicine approaches. In essence, medical imaging is an indispensable tool in modern healthcare, empowering clinicians with invaluable insights into the human body's intricate complexities.

1.2 Problem statement and project overview

Early detection of an infection prior to prosthesis removal (e.g., hips, knees or other areas) would provide significant benefits to patients. Currently, the detection task is carried out only retrospectively with a limited number of methods relying on biometric or other medical data. The automatic detection of a periprosthetic joint infection from tomography imaging is a task never addressed before. This project replicates a method proposed by Guarnera et al. [1] that introduced a novel method for early detection of the hip prosthesis infections analyzing Computed Tomography images.

The dataset has been provided by Rizzoli Orthopedic Institute of Bologna, and it is composed by

CT scans of patients who underwent hip replacement surgery.

Our problem is a good challenge, since we want to detect the infection even if for an expert is difficult to do it. In fact we would like to find patterns in the image of the patients, which are not visible to the human eyes, but are learnable for the network, in order to decide if a patients is really infected or not. In this way we'll reduce the problem to submit aseptic people to the surgery.

The report will proceed in 2 main chapters. Chapter 2 where we will carry out the whole analysis divided into a data preprocessing step (Section 2.1) and a models finetuning step (Section 2.2). Chapter 3 provides the analysis' conclusions and an idea for a future work aimed to improve the infection detection method.

Chapter 2

Infection detection using CNNs

All the code used for this project is available on GitHub [2].

2.1 Data preprocessing

The starting dataset has been preprocessed in order to carry out the analysis. The preprocessing consisted of 6 steps in total which are the following:

1. **Dicom to Numpy matrix conversion**: Since the dataset is composed of CT scans in the dicom format, they have to be converted in an easily manageable fileformat. So in this step each image is first converted to a numpy matrix, thanks to the pydicom library, in order to apply some other transformations before the final PNG conversion. In this phase only axial CT scans have been considered.

2. **Hounsfield prosthesis detection**: Since for each patient there are a lot of axial CT scans of the whole lower part of the body, there have been selected only the images containing the prothesis. This has been done considering a transformation of each pixel value in the Hounsfield scale, thanks to Equation 2.1, and by filtering every image that has at least a pixel value greater than 3000 in the Hounsfield scale.

$$h_p = p * s + i \tag{2.1}$$

   This is done because the metal in the prothesis generate an h_p value higher than 3000.

3. **Bone contour detection and bone image extraction**: Now in order to improve the prediction results a square image of 188x188 with the prothesis as the center has been extracted. This has been done by considering that the h_p values of the bone are values greater than 1000 and by selecting which bone presents the prothesis ($h_p > 3000$).

4. **Image equalization**: Then the pixel range has been normalized in the range $[0, 255]$ and it has been applied the histogram equalization to improve the image contrast.

5. **PNG image export**: Each image has been exported in the png format.

6. **Image resize**: At the end each image has been rescaled in 3 different format: 224x224, 227x227 and 256x256. This has been done in order for the images to be processed by the CNNs.

2.2 Models finetuning

To carry out this benchmark 5 CNN networks have been choosen:

1. SqueezeNet [3]
2. GoogLeNet [4]
3. ResNet18 [5]
4. ResNet50 [6]
5. DarkNet19 [7]

The preprocessed dataset has been divided into 3 sets: training (70%), validation (15%) and testing (15%).

The set of hyperparameters has been choosen after a few trials in order to optimize both training time and performance.

The final set is the following, with the exception of ResNet18, ResNet50 and DarkNet19 that have been trained of 1 epoch.

1. Optimizer: Adam
2. MiniBatchSize: 32
3. MaxEpochs: 2
4. InitialLearnRate: $1e^{-4}$
5. L2Regularization: $5e^{-4}$

The following Figures present on the left the training behaviour of the loss and the accuracy considering both training and validation data and on the right the resulting confusion matrix.

Table 2.1 reports the metrics obtained during the testing phase of the models.

	Parameters	Training time	Accuracy	Precision	Recall	F1-score
SqueezeNet	1.24M	14m 28s	0.9166	0.9867	0.8944	0.9383
GoogLeNet	7M	34m 48s	0.9654	0.9940	0.9569	0.9751
ResNet18	11.7M	18m 19s	0.9760	0.9720	0.9948	0.9833
ResNet50	25.6M	43m 41s	0.9898	0.9914	0.9943	0.9928
DarkNet19	20.8M	34m 40s	0.9821	0.9807	0.9943	0.9875

Table 2.1: Performance metrics of all models.

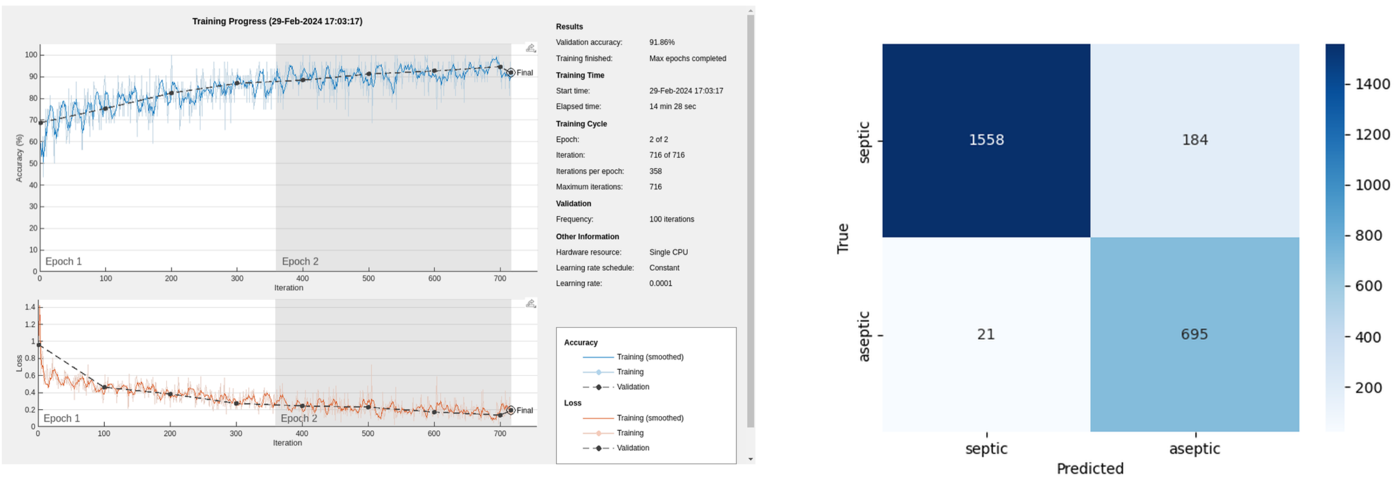

Figure 2.1: SqueezeNet. Left: Training progress. Right: Confusion matrix.

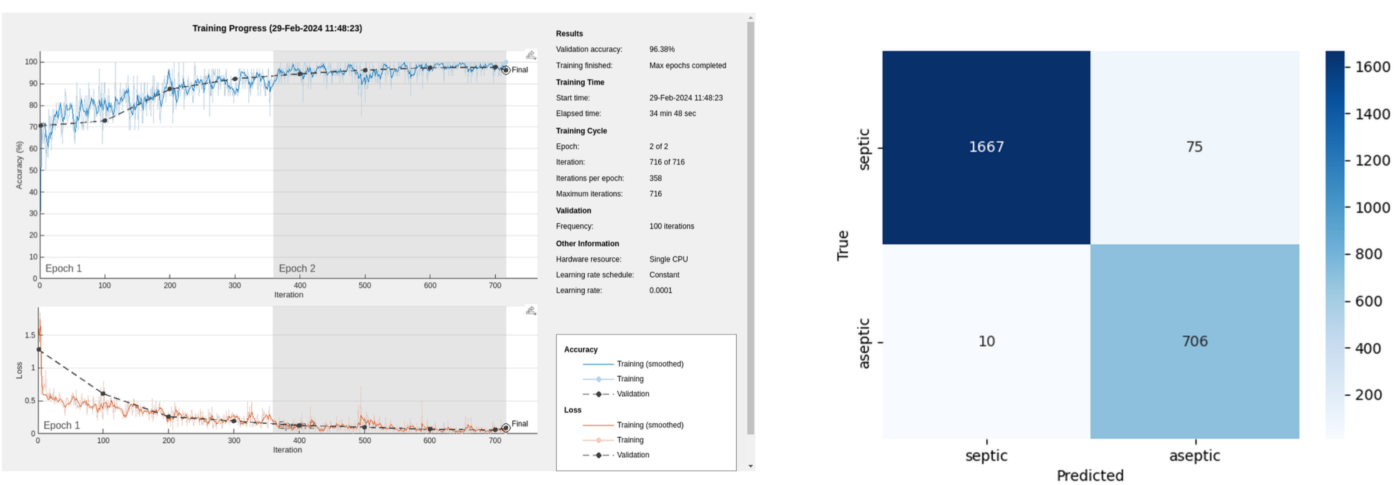

Figure 2.2: GoogLeNet. Left: Training progress. Right: Confusion matrix.

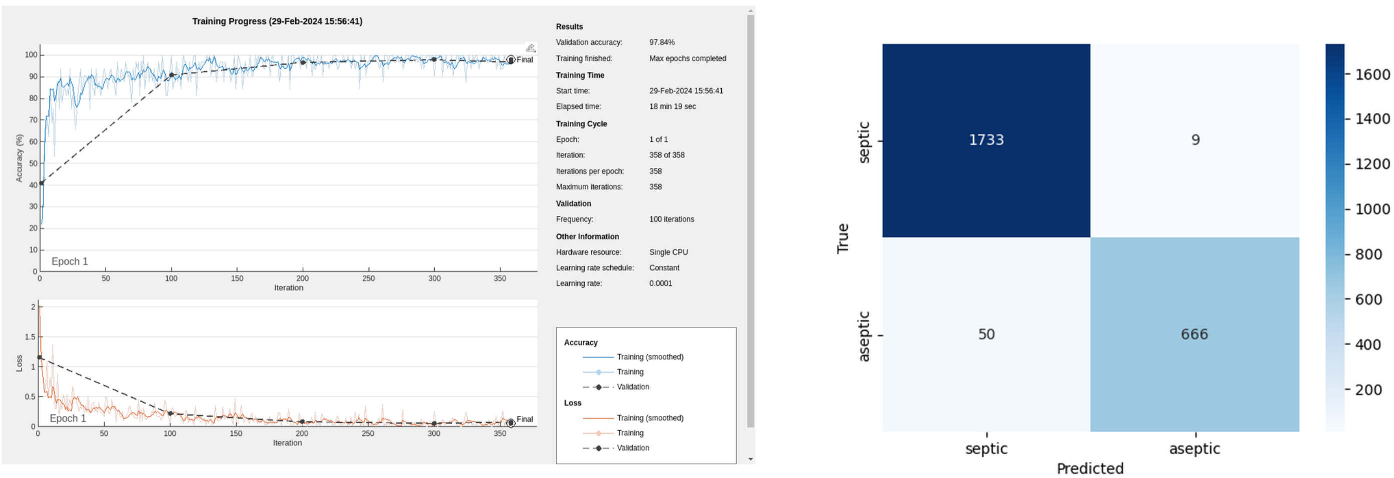

Figure 2.3: ResNet18. Left: Training progress. Right: Confusion matrix.

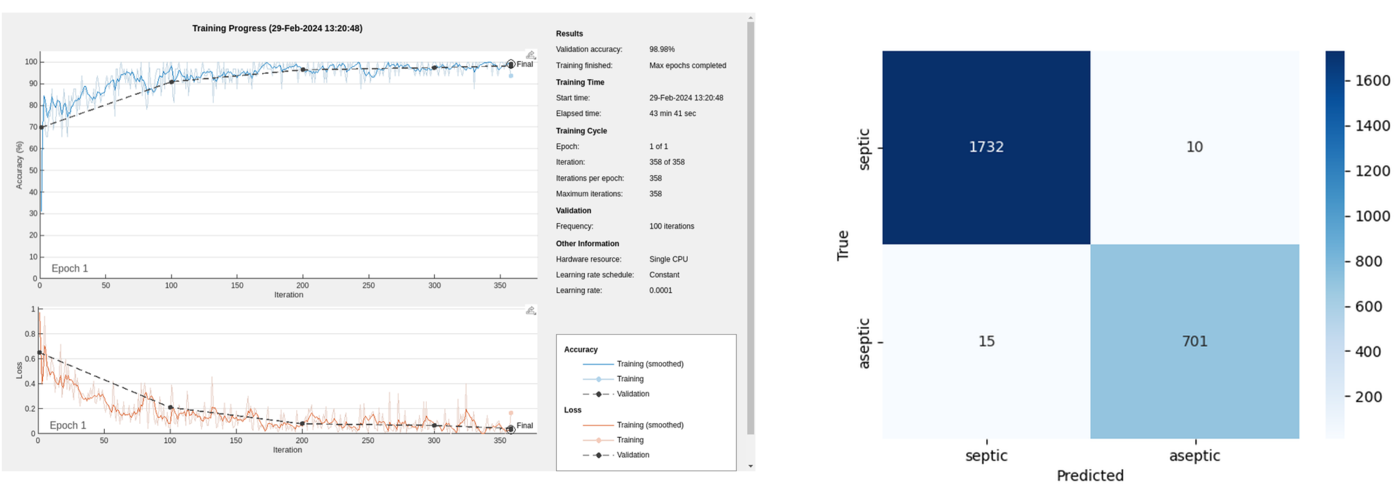

Figure 2.4: ResNet50. Left: Training progress. Right: Confusion matrix.

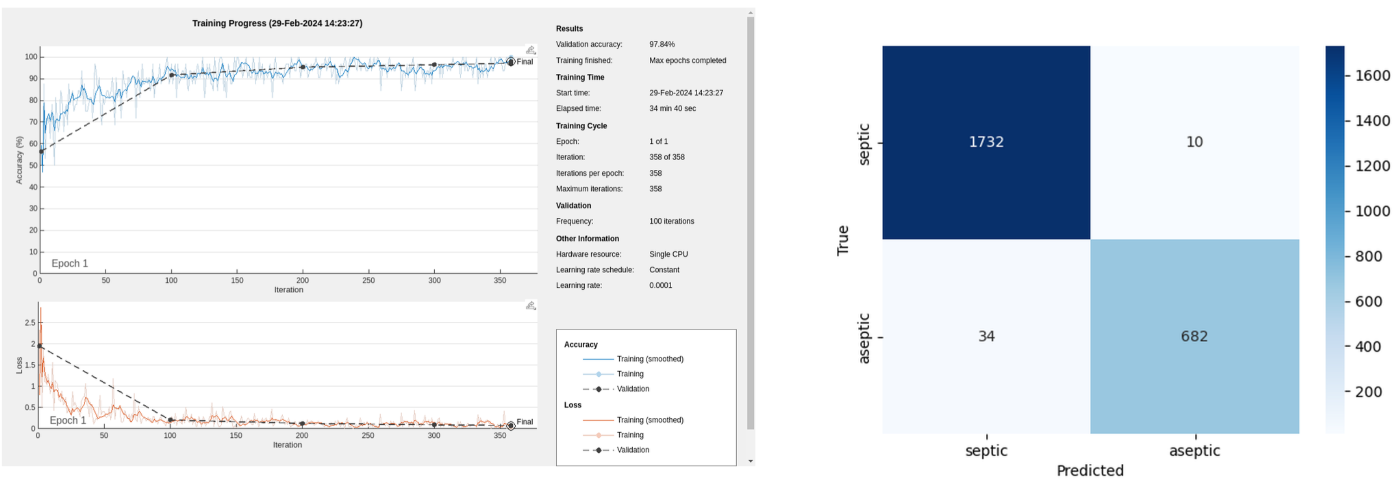

Figure 2.5: Darknet19. Left: Training progress. Right: Confusion matrix.

Chapter 3

Conclusions

In conclusion it's possible to state that:

1. ResNet18 represents a good compromise between performance and complexity. This is due to the residual connections, which make a copy of the signal before passing through the activation function, avoiding the so-called Vanishing Gradient.
2. Very important is GoogLeNet which has the best result in Precision, a metric we are particularly interested in since prothesis removal is a highly invasive treatment. It must be as high as possible so as to minimise cases predicted as septic but really aseptic.
3. The absolute best performing network looking at the F1-score is ResNet50.
4. Many images are labelled as infected but maybe they are normal slices.

Bibliography

[1] F. Guarnera, R. Alessia, O. Giudice, *et al.*, "Early detection of hip periprosthetic joint infections through cnn on computed tomography images," in *Image Analysis and Processing – ICIAP 2023*, vol. 14234, Springer, Sep. 5, 2023, ISBN: 978-3-031-43152-4. DOI: https://doi.org/10.1007/978-3-031-43153-1_12, published.

[2] G. Spadaro, *Giovo17/pji-detection*, GitHub, Feb. 2024. [Online]. Available: https://github.com/Giovo17/pji-detection.

[3] *Squeezenet convolutional neural network - matlab squeezenet - mathworks italia*, it.mathworks.com. [Online]. Available: https://it.mathworks.com/help/deeplearning/ref/squeezenet.html.

[4] *Rete neurale convoluzionale googlenet - matlab googlenet - mathworks italia*, it.mathworks.com. [Online]. Available: https://it.mathworks.com/help/deeplearning/ref/googlenet.html.

[5] *Rete neurale convoluzionale resnet-18 - matlab resnet18 - mathworks italia*, it.mathworks.com. [Online]. Available: https://it.mathworks.com/help/deeplearning/ref/resnet18.html.

[6] *Rete neurale convoluzionale resnet-50 - matlab resnet50 - mathworks italia*, it.mathworks.com. [Online]. Available: https://it.mathworks.com/help/deeplearning/ref/resnet50.html.

[7] *Darknet-19 convolutional neural network - matlab darknet19 - mathworks italia*, it.mathworks.com. [Online]. Available: https://it.mathworks.com/help/deeplearning/ref/darknet19.html.