LUS Images classification with uncertainty detection and image similarity

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Abstract
The proposed multi-stage model for predicting LUS image scores is built using three main components: a multi-class frame classifier, an uncertainty detection model, and a similarity module. The idea is to retrieve similar images and analyze them when the initial prediction is uncertain. The entire project is currently available on GitHub [1].

Introduction

The aim of this project was to develop an alternative way to predict LUS images scores. The first idea that came to my mind was to build something that could be used by doctors, retrieving similar images when the score of a specific frame was not sure in order to "help" with the decision.

The existing methodology consists in scoring all 14 different spots and summing their values. If the result is $< 24/42$, the patient can be left going home because it indicates low probability of worsening.

As explained in the article by S. Roy et al. [2], LUS images are scored as:

- 0: no artifact in the picture;
- 1: at least one vertical artifact (B-line);
- 2: small consolidation below the pleural surface;
- 3: wider hyperechogenic area ($< 50\%$) below the pleural surface.

Frames are taken from videos taken using ultrasound probes and are taken in a maximum of 14 different spots (6 on the front and 8 on the back of the patient), as explained in the article by G. Soldati et al. [3].

My proposed model consists of three main components:

- A multi-class frame classifier that predicts the score of individual LUS images.
- An uncertainty detection model that evaluates the confidence of the initial prediction.
- A similarity module that retrieves similar images and analyzes them when the first model is not confident.

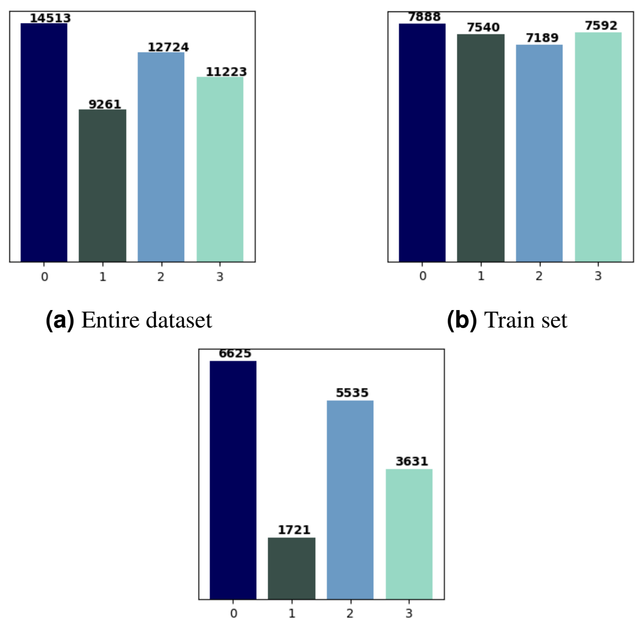
With this multi-stage approach, I aim to improve the accuracy of LUS image scoring and provide technicians with a more reliable tool for diagnosis.

Unfortunately, we will see this idea is probably not effective and results are not encouraging.

1. Data

We have been given a partial dataset from the San Matteo hospital, consisting of 11 patients for a total of ~47k frames.

The dataset score distribution is shown in Figure 1a; at a first glance it could seem to be almost balanced (with only the score 1 that has less frames), but in realty many patients are inherently unbalanced (the score distribution for each patient is shown in Figure 2).



(a) Entire dataset

(b) Train set

(c) Test set

Figure 1. Score distribution in the dataset

1.1 Augmentation

Using the raw dataset got me overfitting even during the first epoch. To address this issue I implemented some transformations taken from the article [2].

In specific, each transformation is activated with a probability of 50%. The set of my augmentation function is:

- affine transformations (translation = $\pm 15\%$, rotation = $\pm 15°$, scaling $\pm 45\%$, and shearing = $\pm 4.5°$)
- multiplication with a constant ($\pm 45\%$)

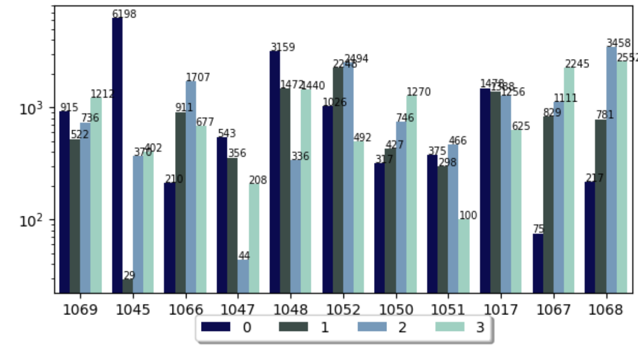


Figure 2. Number of frames for each score for each patient (log scale for better visualization).

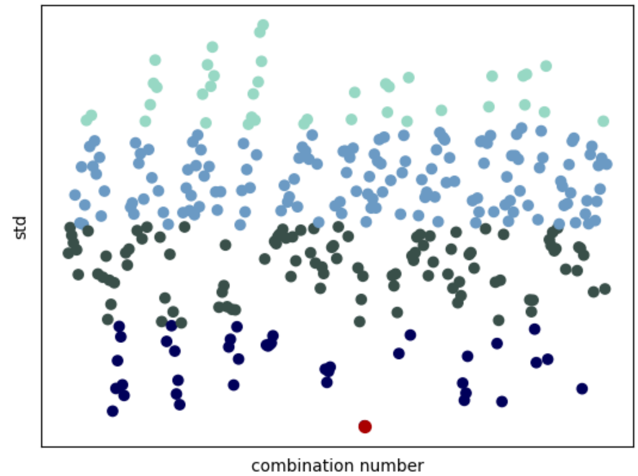


Figure 3. Standard deviation within number of frames per scores of every combination of 8 patients, the red one is the minimum (and so, it is the selected combination).

- Gaussian blurring ($\sigma = 3/4$)
- horizontal flipping ($p = 0.5$)

1.2 Data splitting

Having 11 patients available, my idea was to use 8 of them to train the model and the remaining 3 for testing. This was due to the fact that using a portion of frame for a patient in test and another in train easily leads to overfitting. Even dividing by exams would not been effective since different exams for the same patients still have big correlation.

The first attempt was to test with a *k-fold* approach and then choose the best configuration, but having 165 combinations with $\sim 4h$ per combination it was unfeasible.

So, to balance the dataset I computed the standard deviation within scores for each 8-patients combination and selected the one with lowest std (Figure 3), resulting in the division shown in Figure 1b; the problem now was with the test set, that resulted to be very unbalanced (Figure 1c). After different attempts to balance both sets, I decided to just select an equal number of images for each score from the training patients set of frames to use in the `test_model` method (still, confusion matrices on this report are built using the entire available number of frames).

2. Multi-class classifiers

The first module of my project consists in a deep learning classifier that predicts the score from a frame.

Different pre-trained models have been tested with several different values for my hyperparameters. The training part has been made several times in order to find a model that didn't overfit in the first epoch or didn't stuck in a local minima that always gave one single score.

Frames are very similar, using models too big could get overfitting and using models too small could get no good generalization capability.

2.1 ResNet18

ResNet (Residual Network) is a network introduced by K. He et al. [4] trained on the ImageNet dataset [5].

There are different version of this model based on the number of layers. Looking for a "small" model, ResNet18 was the smallest one and so it has been selected for test.

After many runs, I was able to achieve an accuracy of $\sim 60\%$ in my test set before overfitting. Confusion matrix on the test set can be seen in Figure 4, resulting in an accuracy class-wise that can be seen on Table 1.

0	1	2	3
55.52%	66.88%	40.43%	77.03%

Table 1. Accuracy class-wise of the fine-tuned ResNet18.

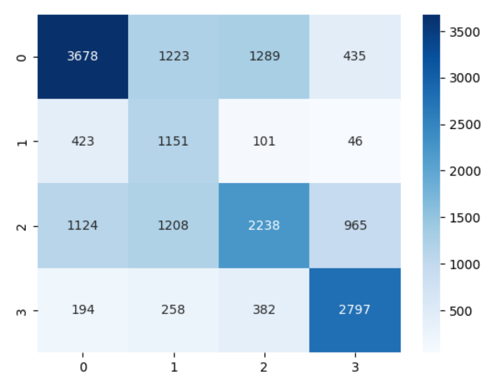


Figure 4. Confusion matrix of the fine-tuned ResNet18.

2.2 VGG16

VGG (Visual Geometry Group) is a convolutional Neural Network built by K. Simonyan, A. Zisserman [6]. It has been trained on a subset of the ImageNet dataset.

Similarly to ResNet, VGG is available with 16 and 18 layers. For the same reasons as above, VGG16 has been selected and tested.

Independently from my fine tuning tries, VGG16 started memorizing the training data even in the first epoch (even having less parameters than ResNet18).

2.3 SqueezeNet

SqueezeNet is a model developed by F. N. Iandola et al. [7] in 2016.

Following the idea to find a compact model, I found out this variation of AlexNet that is still capable of very good performance while requiring less parameters. It has been trained on ImageNet.

SqueezeNet gave me the best results in the early stage of the project, but after refining the fine-tuning of the ResNet, I decided to not use it.

2.4 Built-from-scratch model

I even tried building from scratch a Convolutional Neural Network. I tried different combinations of Convolutional layers but result were very poor, resulting in a path I didn't follow deeper.

3. Binary classifiers

The second goal of this project was to develop a mechanism to determine the confidence of the multi-class frame classifier in its predictions.

Initially, I explored the possibility of using a threshold-based approach; however, during class presentation, we realized that a more sophisticated approach would be interesting to try to capture the behavior of the model in both correct and incorrect predictions. In addition, I observed that the maximum softmax values were similar between correct and incorrect predictions, indicating that a simple threshold approach would not be effective.

As a result, I developed a binary classification model that uses the softmax values of the first model to evaluate the confidence in its predictions.

To train these models, the data has been built by using the trained ResNet18 model on the training set to then save both the softmax values and the correctness (T/F) of the prediction.

3.1 SVC

bla bla bla

3.2 Deep model

bla bla bla

4. Image similarity

The third module of my project consists in an image similarity model.

4.1 Near Duplicate Image Search

bla bla bla

4.2 t-SNE

bla bla bla

4.2.1 Embedding

bla bla bla

4.2.2 Raw Images

bla bla bla

4.2.3 Behavior

bla bla bla Even if this representation is purely based on the first classifier softmax values (and not on visually similar images) it got the best results.

5. Performance analysis

Very very slow due to image similarity.

Bad performance maybe to: binary gets wrong when is correct. Or binary gets 0 and the t-SNE is wrong in exacly those.

6. Conclusions

bla bla bla slow tsne low acc

6.1 Future works

bla bla bla

References

[1] GitHub repository with the project. [Online]. Available: https://github.com/davidemodolo/Lung-Ultrasound-Image-Classifier

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[3] G. Soldati, A. Smargiassi, R. Inchingolo, D. Buonsenso, T. Perrone, D. F. Briganti, S. Perlini, E. Torri, A. Mariani, E. E. Mossolani, F. Tursi, F. Mento, and L. Demi, "Proposal for International Standardization of the Use of Lung Ultrasound for Patients With COVID-19: A Simple, Quantitative, Reproducible Method," *J Ultrasound Med*, vol. 39, no. 7, pp. 1413–1419, Jul 2020.

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7. Data

The template I used for this report can be found on *latextemplates.com* [8].