Final Project for ELEC4840

1 Overall

For the final project, each group is required to select one of the problems in Assignment 2 (Skin lesion classification or CT segmentation) and then further improve the selected task performance via two methods. You need to complete the following tasks:

1. Run a baseline model on the provided dataset (you may use the code from Assignment 2).
2. Propose or implement two methods to improve performance.
3. Write a summary report.
4. Give a presentation in the last class (16 May).

The specific requirements for the project are detailed in the problem statement.

1.1 Submission requirement

1. A report (.pdf, no more than **4 pages**; Reference page do not count in.; Use LNCS Template Link.).
2. Presentation slides (.pdf).
3. Code with the readme file.

1.2 Report Structure

1. Introduction: Introduce your topic and its importance; Give a brief literature review based on the method you choose for improvement.
2. Methodology: Describe the methods you used for performance improvement. Use figures and pseudo codes if necessary.
3. Experiment Results: Use tables and figures to present your results. Use a few paragraphs to discuss your results.
4. Conclusion: Give a brief conclusion on your report.

1.3 Deadline for presentation and submission

PPT submission deadline: May 16, 11:59 pm
Report submission deadline (You can use the extra time after presentation to further refine your written report.): May 20, 11:59 pm
Presentation time: May 16, 14:00 - 17:00

1.4 Grades

Grading policy: Presentation (30%) + Report (70%)
Presentation (30%):

- 20% for attendance
- 5% for well-prepared PPT, including (1) background introduction, (2) method developments, (3) results analysis, and (4) conclusion.
- 5% for well-scheduled presentation: Each group member should present half of the work.

Report (70%):

30%+30% for reproducing satisfactory results of two algorithms. 10% for a well-written report.

An additional 20 points will be given for any **novel** ideas and improvements you have made to improve the performance. To obtain it, please clearly indicate what you have tried and what results you have achieved in your report.

2 Topic Selection

You can select one of the problems in Assignment 2 (Skin lesion classification or CT segmentation) and then further improve the task performance via two methods. You can use the datasets provided in Assignment 2 and the codes you have implemented to finish the project.

3 Possible Directions of Enhancement

Here are some improvement directions that can be applied to both classification and segmentation tasks for your reference. Please notice that you might need to modify some of these method's codes to adapt to your own problem.

3.1 Semi-Supervised Learning

In addition to the fully labeled data provided in the previous assignment, you can also leverage more unlabeled data to expand your data set for a further performance boost. Here, we provide additional unlabeled data for skin lesions (link) and CT images (link) for you to use. Please indicate what and how many unlabeled data have you used in your final report.

You can implement one of the semi-supervised learning algorithms introduced in our class to enhance the performance. The possible solutions are: (1) Classification: Pseudo-Label [6], π model [5], temporal ensembling [5], mean teacher [7], (2) Segmentation: UA-MT [11], UMCT [9], and CPS [3]. In addition to these methods, you can also try to propose some **new** ideas to improve the performance.

3.2 Domain Generalization

The model is likely to suffer performance degradation if the source of the data is diverse. For example, the data is collected from different hospitals, and different hospitals may collect the data using different devices on different patient cohort. Therefore, the model cannot generalize well to these different novel cases.We can leverage domain generalization to mitigate this issue.

You can try to implement one domain generalization (DG) methods introduced in class (FACT [10] for classification task, Dofe [8] for segmentation task or other methods) In addition to these methods, you can also try to propose some **new** ideas to improve the performance.

3.3 Contrastive Learning

Contrastive learning is commonly used to teach models to encode representations by maximizing the distance between differently augmented views of the same data point while minimizing the similarity between representations of different data points, aiming to leverage the inherent structure within the data itself. It is also effective in scenarios where labeled data is scarce.

Several works have explored the essence of contrastive learning and proposed efficient algorithm, such as MOCO [4] and SimCLR [2] for classification and [1] for segmentation. You can refer to those researches and apply contrastive learning to improve your model.

References

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