Meta-Learning for Breast Cancer Prediction

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Introduction

Using the concept of meta-learning, we will create a Machine Learning (ML) model for breast cancer prediction. Breast cancer is the second leading cause of cancer deaths among women in the United States, and around 240,000 cases are diagnosed every year. [1] There are many external factors which contribute to the risk of getting breast cancer, which include sex and increasing age. For one, hereditary traits play a significant role in determining breast cancer risk, such as mutations in the BRCA1 and BRCA2 gene. It has been shown that while 12% of women have a chance of developing breast cancer sometime during their lives, 72% of women who inherit a harmful BRCA1 mutation and 69% of women who inherit a harmful BRCA2 mutation will develop breast cancer by the age of 80. [2] However, it is not feasible to try and diagnose breast cancer in this fashion, especially in regions with limited resources.

Another way of screening for breast cancer is through the standard approach -- a mammogram. This is an accessible way for women to catch breast cancer in the early stages, which can improve their chances of remission.[3] If a mass is detected, the physician is likely to request a fine needle aspirate (FNA), a type of biopsy procedure.[4] This procedure is often limited by the subjective interpretation of the mass, decreasing the accuracy of the diagnosis. By coupling ML techniques with digital image analysis, we can create a model to increase the accuracy of classification given features derived from a FNA procedure.[5]

Meta-learning is the idea of specializing an update rule to a problem by the process of learning. ML tasks can be expressed as optimizing an objective function. Gradient descent serves as a standard approach for minimizing differentiable functions in a sequence of updates following the form:

$$\theta_{t+1} = \theta_t - \alpha_t \nabla f(\theta_t)$$

Specialization to subclasses of problems is how performance can be improved. For example, in the realm of deep learning AI, methods are specialized to handle high-dimensional, non-convex problems. As such, current research on optimization involves designing update rules that are optimized for certain subsets of problems.

Meta-learning involves this concept: instead of researching extensively to construct an adequate update rule for a certain problem, one can replace the rule with a learned update rule, which dynamically updates with each iteration and is specified by its own parameters. In the context of breast cancer prediction, which is affected by many external and genetic factors, we can utilize meta-learning to derive an update rule which best suits this problem. [6]

Previous Work

Using ML to assist with the diagnosis of cancer - specifically breast cancer - has been a field of interest since the 1990s. Particularly, FNA data has been used to construct such ML models due to the apparently high association between FNA results and breast cancer diagnosis. For example, digital FNA data was processed through a ML algorithm to correctly diagnose a fairly substantial number of new patients [7]. Furthermore, another study compared the use of Radial Basis Function (RBF) neural network and Multilayer Perceptron (MLP) algorithms for breast cancer diagnosis, once again using FNA data to construct the models [8]. The study demonstrated that such network models were better and faster in terms of the prediction of the breast cancer diagnosis on new data than the then standard use of logistic regression.

However, we have only recently experienced a rise in the data-drive design of ML algorithms for the application of breast cancer diagnosis. Moreover, as far as we know, the ideas for a meta-learning algorithm described earlier have not been applied to such an application.

Research Question

Since breast cancer diagnosis is a relatively new application of meta-learning, we seek to answer the following question of interest:

- Can we effectively apply the described meta-learning technique to improve existing ML models that are used for breast cancer diagnosis?

We also consider a secondary question throughout the development of our project:

- Given a particular meta-learning technique, what is the degree of improvement between different base ML models?

Plan of attack

First, we make the assumption that physical attributes of a mass can indicate if it is malignant or benign. Because we have about 4 weeks to complete this project, we break down our plan on a weekly basis:

Week 1: *Preprocessing of Wisconsin dataset, gathering additional datasets, and analyzing papers*

We use the Wisconsin breast cancer dataset from the study comparing RBF and MLP models and instead repurpose it to examine the effectiveness of adding meta-learning to these existing models [8]. If possible, we will try to find other FMA datasets to add to existing data. We will also take this time to fully understand the RBF and MLP models from the study and as well as how meta-learning was implemented in the paper *Learning to Learn by Gradient Descent by Gradient Descent* [6].

Week 2: *Research and implementation of meta-learning techniques and RBF/MLP models*

We will create and do initial tests for RBF and MLP models on the FMA datasets that we have already preprocessed. The meta-learning should allow for a more effective optimizer for the model, and we should be able to compare models that utilize meta-learning to ones that use out-of-the-box optimizers.

Week 3: *Testing and compilation of results for presentation/paper, fine tuning models*

By now we should have sufficient data and test results to make conclusions about our study. We should be able to start writing report and create the presentation.

Week 4: *Final polishing of paper and presentation*

We will spend this time doing any final tests and prepare the presentation and papers for submission.

References

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