Project Proposal
Transfer Learning in CNNs

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***Abstract*—Machine Learning and Data Mining have been used in various real-world applications. This is due to the increase in the data available people can train from. With the rise of data collection, machine learning has achieved meaningful advances in classification, regression, and clustering. However, many Machine Learning methods work well under a common premise: The training and test data are drawn from the same domain. In real-world scenarios, this is not always the case. There are times where gathering and processing data is expensive and difficult to collect. Also, when the amount of data is not significant to learn from, there needs to be a way to transfer knowledge from already previously learned domain. This is where Transfer Learning can help alleviate and solve these problems.**

1. Proposal

Convolution Neural Networks are a great example of where we can use Transfer Learning to get a learned function to make prediction. Using pretrained weights from layers from a model trained on one task, it can benefit and improve the performance in another task. In computer vision problems, it has become a common practice to perform image classification with ImageNet and tune the features to the new target task [1]. The idea of using pretrained models with their weights is not a new idea but to what extend can it be beneficial.

In my project, I want to explore how Transfer Learning can be applied and to what extend can it benefit in medical image classification. In particular, I will be using a recent dataset in skin cancer detection, HAM10000 MINST dataset [2]. It consists of 10,015 dermatoscopic images of common pigmented skin lesions. The dataset has seven classes in which each picture belongs to one class. For my project, I want to test which layers of network should be transferred and which layers should be frozen from training. To test this, I will be testing each layer of the network with a base model and monitoring the performance of the accuracy.

Testing the ability to transfer features between general to specific tasks like ImageNet classification, which is trained on 1.2 million images with 1000 object classes to a cancer detection classification can show how we can use transfer knowledge from a large task to smaller yet unrelated task. Transfer Learning relies on tasks to have a shared or related task to have positive effect on performance. If we show that we can reuse the weights from ImageNet for the classification, then we can show that starting training from an unrelated task is better than random initialized weights.

After determining which layers are best to transfer parameters and which layers should be frozen, I want to test the model on another medical image classification dataset. This will show if any knowledge of skin lesions can be applied to other cancer detections. I will be testing this against ImageNet weights for the same model and a model with random initialized weights. The results will show if it is possible to transfer knowledge of cancer detection from one task to another.

TABLE 1. PROJECT TIMELINE

Date	Task to Complete
Jan. 31	Finish Project Proposal and Timeline
Feb. 12	Have results to compare to random weights vs. ImageNet weights
Feb. 19	Find the best performance with fine-tuning
Feb. 25	Find another medical image dataset and compare model results
Mar. 11	Analyze how well features were transfer from task
Mar. 18	Research a way to test and quantify if a given layer is general vs. specific
Apr. 8	Test networks layers to find which layers are general vs. specific to medical image classification
Apr. 22	Finish results and paper

References

[1] Mi-Young Huh, Pulkit Agrawal, and Alexei A. Efros. What makes imagenet good for transfer learning? *CoRR*, abs/1608.08614, 2016.

[2] Philipp Tschandl. The ham10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions, 2018.