Machine Learning Engineer Nanodegree

Capstone Proposal

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Proposal

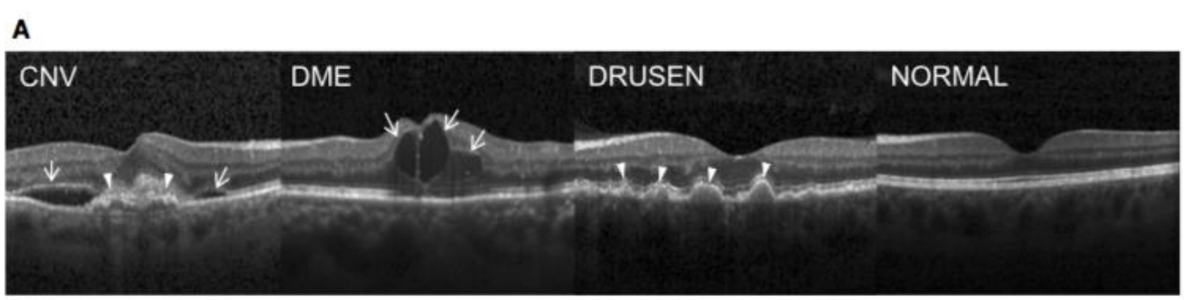
Domain Background

In this Project I will be working the Retinal Optical Coherence Tomography and how it is used to detect different retinal diseases.

Optical coherence tomography (OCT) is a non-invasive imaging test. OCT uses light waves to take cross-section pictures of your retina.

With OCT, your ophthalmologist can see each of the retina's distinctive layers. This allows your ophthalmologist to map and measure their thickness. These measurements help with diagnosis. They also provide treatment guidance for glaucoma and diseases of the retina. These retinal diseases include age-related macular degeneration (AMD) and diabetic eye disease.

Retinal optical coherence tomography (OCT) is an imaging technique used to capture high-resolution cross sections of the retinas of living patients. Approximately 30 million OCT scans are performed each year, and the analysis and interpretation of these images takes up a significant amount of time (Swanson and Fujimoto, 2017).



(A) (Far left) choroidal neovascularization (CNV) with neovascular membrane (white arrowheads) and associated subretinal fluid (arrows). (Middle left) Diabetic macular edema (DME) with retinal-thickening-associated intraretinal fluid (arrows). (Middle right) Multiple drusen (arrowheads) present in early AMD. (Far right) Normal retina with preserved foveal contour and absence of any retinal fluid/edema.

Citations:

Mooney, Paul. "Retinal OCT Images (Optical Coherence Tomography)." *Kaggle*, 25 Mar. 2018, www.kaggle.com/paultimothymooney/kermany2018.

"Optical Coherence Tomography." *EyeWiki*, 20 Jan. 2015, eyewiki.aao.org/Optical_Coherence_Tomography.

Kermany, D.S., Goldbaum, M., Cai, W., Valentim, C.C.S., Liang, H., Baxter, S.L., McKeown, A., Yang, G., Wu, X., Yan, F., Dong, J., Prasadha, M.K., Pei, J., Ting, M.Y.L., Zhu, J., Li, C., Hewett, S., Dong, J., Ziyar, I., Shi, A., Zhang, R., Zheng, L., Hou, R., Shi, W., Fu, X., Duan, Y., Huu, V.A.N., Wen, C., Zhang, E.D., Zhang, C.L., Li, O., Wang, X., Singer, M.A., Sun, X., Xu, J., Tafreshi, A., Lewis, M.A., Xia, H. and Zhang, K. (2018). Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. *Cell*, [online] 172(5), p.1122–1131.e9. Available at: https://www.cell.com/cell/fulltext/S0092-8674(18)30154-5 [Accessed 6 Apr. 2019].

Problem Statement

The implementation of clinical-decision support algorithms for medical imaging faces challenges with reliability and interpretability. Here, we establish a diagnostic tool based on a deep-learning framework for the screening of patients with common treatable blinding retinal diseases. Our framework utilizes transfer learning, which trains a neural network with a fraction of the data of conventional approaches. Applying this approach to a dataset of optical coherence tomography images, we demonstrate performance comparable to that of human experts in classifying age-related macular degeneration and diabetic macular edema.

Datasets and Inputs

The dataset is organized into 3 folders (train, test, Val) and contains subfolders for each image category (NORMAL, CNV, DME, DRUSEN). There are 84,495 X-Ray images (JPEG) and 4 categories (NORMAL, CNV, DME, DRUSEN). Images are labeled as (disease)-(randomized patient ID) -(image number by this patient) and split into 4 directories: CNV, DME, DRUSEN, and NORMAL.

Optical coherence tomography (OCT) images (Spectralis OCT, Heidelberg Engineering, Germany) were selected from retrospective cohorts of adult patients from the Shiley Eye Institute of the University of California San Diego, the California Retinal Research Foundation, Medical Center Ophthalmology Associates, the Shanghai First People's Hospital, and Beijing Tongren Eye Center between July 1, 2013 and March 1, 2017.

Dataset: Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification

http://dx.doi.org/10.17632/rscbjbr9sj.2#file-9e8f7acf-7d3a-487f-8eb5-0bd3255b9685

Solution Statement

The development of convolutional neural network layers has allowed for significant gains in the ability to classify images and detect objects in a picture (Krizhevsky et al., 2017, Zeiler and Fergus, 2014). These are multiple processing layers to which image analysis filters, or convolutions, are applied. The abstracted representation of images within each layer is constructed by systematically convolving multiple filters across the image, producing a feature map that is used as input to the following layer. This architecture makes it possible to process images in the form of pixels as input and to give the desired classification as output. The image-to-classification approach in one classifier replaces the multiple steps of previous image analysis methods.

One method of addressing a lack of data in a given domain is to leverage data from a similar domain, a technique known as transfer learning. Transfer learning has proven to be a highly effective technique, particularly when faced with domains with limited data (Donahue et al., 2013, Razavian et al., 2014, Yosinski et al., 2014). Rather than training a completely blank network, by using a feed-forward approach to fix the weights in the lower levels already optimized to recognize the structures found in images in general and retraining the weights of the upper levels with back propagation, the model can recognize the distinguishing features of a specific category of images, such as images of the eye, much faster and with significantly fewer training examples and less computational power (Figure 1).

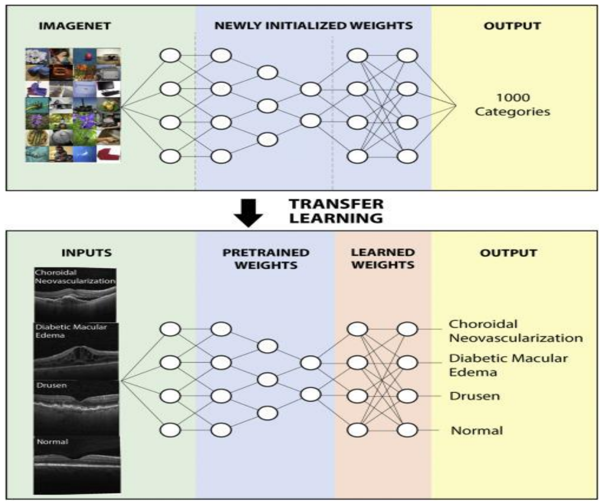


Figure 1 Schematic of a Convolutional Neural Network

In this study, we sought to develop an effective transfer learning algorithm to process medical images to provide an accurate and timely diagnosis of key pathology in each image. The primary illustration of this technique involved optical coherence tomography (OCT) images of the retina, but the algorithm was also tested in a cohort of pediatric chest radiographs to validate the generalizability of this technique across multiple imaging modalities.

Benchmark Model

We will compare our results against the Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning (https://www.cell.com/cell/fulltext/S0092-8674(18)30154-5) which has different metrics such as confusion matrix, accuracy, precision, recall and AUC.

Evaluation Metrics

We will compute the accuracy, confusion matrix, precision, recall and AUC for the model and compare the results with the benchmark model.

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made}$$

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

Project Design

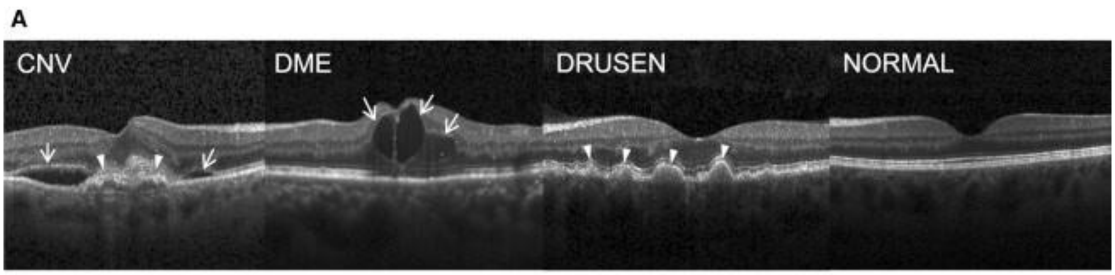
First, we will import the dataset which contains the images of the 4 classes which will be used by the model to predict. We pre-process the data when using TensorFlow as backend, Keras CNNs require 4D array as input, with shape

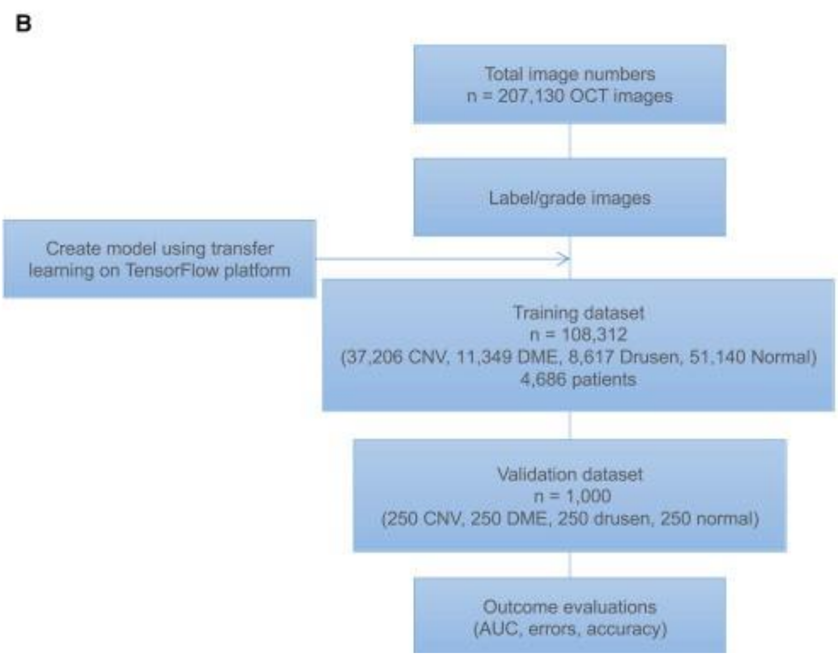
$$(\text{nb\_samples},\ \text{rows},\ \text{columns},\ \text{channels}),$$

where nb_samples correspond to the total number of images (or samples), and rows, columns, and channels correspond to the number of rows, columns, and channels for each image, respectively. Then we can normalize this input to feed it to the Neural network.

Now the input is ready to feed to the Convolution Neural Network algorithm which we plan to implement from scratch and make a note of different metrics.

After this we will use one of the transfer learning (Inception) algorithms and where we will not include the final layer. Use this algorithm to train against out training set and then use validation set to validate the results.





Finally, we can use the model to predict against the test set to check the accuracy of our model.