ADDENDUM

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TITLE: Detecting Nodular Basal Cell Carcinoma Using Deep Learning Image Segmentation
CATEGORY: Translational Medicine

Research Plan/Project Summary

a. Rationale

With over 4.3 million new cases in the U.S. every year, basal cell carcinoma (BCC), caused largely by sun exposure, is the most common form of skin cancer. There have been previous attempts at diagnosing skin cancer using machine learning, but many use traditional, non-deep learning approaches such as random forest to do so, while others address cancers from images of the epidermis, not the pathology image [2, 3]. As a result, different skin tones and lesion shapes lead to varied results given the image. One way to address the need for standardized, expedited diagnosis, is through an automated diagnostic machine designed to identify BCC given pathology images. It will utilize a deep neural network image segmentation model called U-Net to train on the dataset and their corresponding masks, which can learn to highlight these nodules in pathology images by outputting a computer-generated mask. The ability of the model to identify even outlines and parts of BCC is promising in terms of versatility as testing images begin to span across image types. By creating a novel surgeon interface for rapid pathological assessment and machine learning diagnostics for pathological features, the BCC diagnosis process will be expedited and standardized.

b. Research Question(s)/Hypothesis(es)/Engineering Goal(s)/Expected Outcome(s)

How can we automate the diagnosis of basal cell carcinoma from the pathology image? The engineering goal is to create an automated skin cancer detector using a deep learning approach and pathology images.

c. Detailed description of methods or procedures, Risk and Safety Analysis, Data Analysis

Detailed description of methods or procedures:

In order to train a machine learning image segmentation model, training image data and correlating ground truth masks will be used. A mask is an image that has a single value (e.g. 1 or 2) designating each pixel as in a particular region (e.g. normal or cancer), which acts as a label in segmentation algorithms. I will collect training image data consists of nodular basal cell carcinoma pathology images that were found on Google. This dataset will then be processed using a MATLAB algorithm that allows the user to manually crop each image into smaller, more specific square regions of the larger, original image, which allowed for a way to increase the data by producing more high quality and varied images of distinct BCC nodes. To standardize the training data before mask creation, the cropped, hand selected images will be scaled to be 1500x1500x3 pixel JPEGs. A mask labeller that enables a user to generate 1127x1127x1 square pixel gold standard masks of 0 and 1 for background and BCC, respectively will be used. By making the images larger than the U-Net requirement of 1127x1127 pixels, possible discrepancies along the edges of the tumor masks can be validated and checked manually in an effort to preserve the shape and cropped edge of the tumors within the masks.

U-Net is the state-of-the-art architecture for image segmentation in medical imaging. With two paths, the U-Net architecture begins with the contracting path (or encoder) to "capture context and a symmetric expanding path that enables precise localization"[6]. This encoder consists of standard convolutional and max pooling layers found in convolutional neural networks. The second path is known as the symmetric expanding path (or decoder), which, using transposed convolutions that "enables precise localization"[6]. As a result, the U-Net is a Fully Convolutional Network, which given an input image tile, is able to produce an output segmentation map that predicts each pixel's class.

Following the results of the experiment mentioned above, where it was found that the results are optimized when the image originates from the same image and microscope, a slightly different approach to increase the model's accuracy and versatility was used. A second test used a single training image that was augmented into five additional, slightly different images, using various techniques such as cropping and flipping to increase the diversity in the data. The U-Net architecture, with a data-augmentation-focused training strategy, is known to perform well with limited data [2]. Testing was on image from the same tissue. Furthermore, a third test utilized a new dataset of images of larger, higher quality BCC, each cropped into *n* images. The model was then trained on *n-1* sub images and tested on *nth* image.

Risk and Safety Analysis:

This project should be extremely low-risk—computers are the only tools being used. Looking at a computer screen for significant periods of time may cause headache or nausea, but this is highly unlikely if breaks are taken.

Data analysis:

The masks will output clearly the highlighted regions of detected tumor. To quantify the results, sensitivity and specificity will be calculated using the permutation of two binary lists (0,1), each showing either a true positive, true negative, false positive, or false negative. Sensitivity (or true positive rate, shows the probability of detection) is a number between 0 and 1. Specificity (or true negative rate) is also a number between 0 and 1 and shows the proportion of actual negatives that are correctly identified. Together, they can measure the performance of a binary classifier like the automated BCC model.

d. Bibliography

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