CALIFORNIA SCIENCE & ENGINEERING FAIR
2019 PROJECT SUMMARY

Name(s)

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Project Number

S0825

Project Title

SkinSight: A Novel Implementation of a Convolutional Neural Network to Recognize Skin Diseases

Abstract

Objectives

Only 35% of skin disease biopsies are performed by dermatologists, and non dermatologists only correctly diagnose skin diseases with 23.9% accuracy. Many methods have tried to solve this issue, but most are computationally heavy, while algorithms that can segment lesions have not been used for diagnosis. This project aims to design a computationally light and effective convolutional neural network (CNN) to diagnose skin lesions while also evaluating two common deep learning based approaches, Mask R-CNN and FCN, for multiclass segmentation against results from the ISIC 2018 Challenge: Skin Lesion Analysis Towards Melanoma Detection.

Methods

Our physical materials included a laptop with Anaconda installed on it. The dataset was provided by DermnetNZ, but since there are only 4374 images, we used data augmentation to make it larger. To train Mask R-CNN and FCN, we produced a dataset of 520 images with pixelwise masks identifying the lesions. Then, we used code for Mask R-CNN and FCN from Matterport and Sagippel s Github, respectively, and for transfer learning, we used the Tensorflow Image Retraining Tutorial. For our CNN, we used transfer learning, where we took an existing CNN, Inception-v3, and added a classification layer. To improve accuracy, we grouped diseases by physical traits. For Mask R-CNN, we wrote a new supervision and dataset loading file and trained it for 60 epochs. For FCN, it trained for approximately 40 epochs.

Results

We found that as the size of each group for our transfer learning decreased, accuracy improved, but human error increased when choosing the correct group. As the number of training steps increased, the accuracy increased. For the segmentation techniques, the Mask R-CNN achieved 0.9053 mean average precision and a 0.7532 Jaccard Index while the FCN achieved a 0.7241 Jaccard Index.

Conclusions

Having 15 diseases per group and 16000 training steps offered the best cost/efficiency tradeoff for its 86.5% balanced accuracy and 0.85 average F1 score. FCN was less effective than Mask R-CNN because it introduced interference into its predictions, leading to a lower Jaccard Index. The transfer learning and segmentation methods we tested in this study achieved comparable results to studies in the ISIC 2018 Challenge which achieved 85.3% balanced accuracy and 0.813 Jaccard Index, proving the feasibility of both transfer learning and multiclass segmentation.

Summary Statement

We implemented an effective and efficient transfer learning approach to skin lesion diagnostics, and we also proved that multiclass segmentation of skin lesions is feasible, with the best method of doing so being Mask R-CNN.

Help Received

None. We worked on the project by ourselves.