DS 6050 Project Proposal

DIRECTIONS

Sections

1. Motivation: What problem are you tackling? Is this an application or a theoretical result?
2. Dataset: Presenting a URL to a dataset you found (and a description)
3. Related work: At least one example of prior methodology on the topic is a valuable addition.
4. Intended experiments: What experiments are you planning to run? How do you plan to evaluate your machine learning algorithm?

Submission Instructions

Your proposal should be submitted as a PDF (two page maximum) and include:

- The title of the project
- The project category
- Your full name and UVA ID
- **A 300-500 word description of what you plan to do**

PROPOSAL

Title

Employing Neural Networks for Early Detection of Ocular Diseases

Category

Multi-Class Classification, Medicine

Names

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Motivation

As of 2021, the World Health Organization (WHO) estimates over two billion people suffer from visual impairment, and nearly half of these cases were preventable, or have not yet been treated.[1] Neural networks can mitigate challenges inherent in diagnosis, using advanced classification algorithms to enable early detection and correction.

Dataset

The Ocular Disease Intelligent Recognition (ODIR) dataset on Kaggle provided by Peking University and Shanggong Medical Technology Co. Ltd. includes 5000 color fundus images of retinal tissue taken with various camera brands, including Canon, Zeis, and Kowa. Pictures of the right and left eyes of patients are labeled with at one of eight diagnoses – normal (1140 cases), diabetes (1128), glaucoma (215), cataract (212), age-related macular degeneration (164), hypertension (103), myopia (174), and other diseases/abnormalities (979) – as well as patients' age and sex.[2,3]

Related Work

Multiple research teams have explored solutions to classification with the ODIR dataset. Jordi et al. (2019) converted the problem into a multi-class classification problem and found a neural network with a VGG16 backbone outperformed an Inception-based model in terms of accuracy,[4] a result Gour et al. (2020) confirmed when tackling the full the multi-class and multi-label problem presented using ResNet, InceptionV3, MobileNet, and VGG16.[5] Li et al. (2020) developed a Dense Correlation Network (DCNet) with a ResNet Convolutional Neural Network (CNN), a Spatial Correlation Module (SCM), and a classifier.[3] Wang et al. (2020) used the pre-trained EfficientNet and an ensemble of two weak classifiers on the color dataset and a rescaled gray-scale dataset.[6] He et al. (2021) implemented a "knowledge distillation-based optimization strategy" to transfer learning from a complex teacher model to a lightweight student model using both the fundus images and clinical data (patient age and sex and diagnostic key words).[7] Islam et al. (2019) created a custom – yet fairly standard – CNN,[8] while Demir et. al (2021) combined a R-CNN+LSTM (long short-term memory) with feature selection algorithm NCAR (Neighborhood Components Analysis - ReliefF).[9] This last and most recent approach performed comparably or outperformed others in terms of AUC (area under the curve), F-score, and accuracy.[9]

Intended Experiments

To expand upon previous research, we will assess the performance of ensembles of pre-trained models, including VGG16, ResNet, InceptionV3, MobileNet, and EfficientNet, along with recurrent neural networks (RNNs) with LSTM layers as used by Demir et al (2021).[9] With regards to preprocessing, we will augment the data via image transformations due to the relatively small size of the ODIR dataset. We will also attempt to address the class imbalance in the ODIR data using some of the methods found in the survey describing this issue in deep learning by Johnson et al. (2019), such as random over-sampling and under-sampling and dynamic sampling,[10] and/or by applying disproportionate amounts of data augmentation based on class prevalence. We will incorporate stochastic gradient descent (with momentum) and Adam optimization, as these proved successful in past approaches. Evaluation metrics will include categorical cross-entropy loss; overall and class-specific AUC (area under the curve) and F score; and kappa (to determine model robustness with class imbalances).[7]

Word Count of Proposal: ~ 500 words (per instructions)

Citations

1. "Vision Impairment and Blindness." World Health Organization. World Health Organization, 2021. https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment.

2. Larxel. "Ocular Disease Recognition." Kaggle, September 24, 2020. https://www.kaggle.com/andrewmvd/ocular-disease-recognition-odir5k?select=preprocessed_images.

3. Li, Cheng, Jin Ye, Junjun He, Shanshan Wang, Yu Qiao, and Lixu Gu. "Dense Correlation Network for Automated Multi-Label Ocular Disease Detection with Paired Color Fundus Photographs." *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*, 2020. https://doi.org/10.1109/isbi45749.2020.9098340.

4. JordiCorbilla. "Jordicorbilla/Ocular-Disease-Intelligent-Recognition-Deep-Learning: Odir-2019. Ocular Disease Intelligent Recognition through Deep Learning Architectures." GitHub. Accessed March 6, 2022. https://github.com/JordiCorbilla/ocular-disease-intelligent-recognition-deep-learning.

5. Gour, Neha, and Pritee Khanna. "Multi-Class Multi-Label Ophthalmological Disease Detection Using Transfer Learning Based Convolutional Neural Network." *Biomedical Signal Processing and Control* 66 (2021): 102329. https://doi.org/10.1016/j.bspc.2020.102329.

6. Wang, Jing, Liu Yang, Zhanqiang Huo, Weifeng He, and Junwei Luo. "Multi-Label Classification of Fundus Images with EfficientNet." *IEEE Access* 8 (2020): 212499–508. https://doi.org/10.1109/access.2020.3040275.

7. He, Junjun, Cheng Li, Jin Ye, Yu Qiao, and Lixu Gu. "Self-Speculation of Clinical Features Based on Knowledge Distillation for Accurate Ocular Disease Classification." *Biomedical Signal Processing and Control* 67 (2021): 102491. https://doi.org/10.1016/j.bspc.2021.102491.

8. Islam, Md. Tariqul, Sheikh Asif Imran, Asiful Arefeen, Mahmudul Hasan, and Celia Shahnaz. "Source and Camera Independent Ophthalmic Disease Recognition from Fundus Image Using Neural Network." *2019 IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON)*, 2019. https://doi.org/10.1109/spicscon48833.2019.9065162.

9. Demir, Fatih, and Burak Taşcı. "An Effective and Robust Approach Based on R-CNN+LSTM Model and NCAR Feature Selection for Ophthalmological Disease Detection from Fundus Images." *Journal of Personalized Medicine* 11, no. 12 (2021): 1276. https://doi.org/10.3390/jpm11121276.

10. Johnson, Justin M., and Taghi M. Khoshgoftaar. "Survey on Deep Learning with Class Imbalance." *Journal of Big Data* 6, no. 1 (2019). https://doi.org/10.1186/s40537-019-0192-5.