Risk Analysis of Skin Cancer using Deep Learning

Matthew May, Stefano Fenu, Thanh Dang, Apurv Verma

March 1, 2016

Abstract

Skin cancer is the most common form of cancer, accounting for 40% of cases globally. More than 8,500 people in the US are diagnosed with skin cancer everyday. Melanoma rates in the United States have doubled from 1982 to 2011. The survival rate of people with it depends on when they start treatment. The cure rate is very high with early prognosis. The curability is as high as 92% if the cancer is detected early. The prognosis is less favorable if it has spread to other parts of the body. Deep convolutional neural networks have led to new breakthroughs in image classification. Advancement in neural network frameworks and GPU based computing has allowed us to train deeper and deeper networks. We aim to exploit these advancements and apply it to the problem of early skin cancer detection.

1 Problem Statement

To build a platform where dermatologists can easily scan through the cancer prone patients. The system uses deep learning techniques in the background to learn from thousands of images and associates a risk score with each uploaded image. The value of the score can be used to differentiate between malign and benign cases. We also aim to train a model for multi-class classification among the 23 classes.

2 Current Approaches/Survey

It is an unfortunate fact of the healthcare system that it spends more in research on expensive treatments for late-stage diseased individuals than developing scalable and cost-effective early screening methods. To the best of our knowledge, no one has attempted to build such a system.

It is only recently that neural networks have been used for the problem of skin cancer classification. Much of the earlier work focussed on extracting features based on image processing techniques to do the classification. In [9], Lee and Chen use low level feature comparison for detecting different cancer types. In [7], the authors use a combination of neural networks and sophisticated image processing and feature extraction techniques to achieve a fast and reliable diagnosis. They were able to obtain a 90% correct classification of malignant and benign skin lesions from the DANAOS data collection. In [10] the authors use a multilayer perceptron to classify melanoma.

There have also been techniques like [4], [12] which combine spectroscopy data with neural networks. These techniques are only plausible in a lab setting with appropriate instruments. The novelty of our technique is that it relies solely on image data. These images can be captured by an individual using smartphones and does not require any specialized pathology skills. The user could get a reminder to upload the image to the website on a periodic basis and the dermatologist could monitor high risk patients easily using our system.

The most recent work which is related to our current work was done by Andre, Kuprel and Sebastian Thrun at Stanford. [3]. The approach used by them is an ensemble of 5 models (VGG16-1, VGG16-2, VGG16-3, VGG19-1, and VGG19-2) that classify among the 23 classes. We try to achieve a better accuracy over their model and also build a system for dermatologists to efficiently manage their patients.

3 Salient Features and Innovation

- A model which can work with images captured through webcams, smartphones or other day-to-day shops medical devices.

- An interface for patients to upload their image periodically so the clinician can monitor the lesion outside the clinic

- An interface for the clinician to view high risk patients at the top of their feed. The high risk patients are found out by passing the uploaded image through the learnt network.

- The system also displays similar lesions as to provide an explanation of why it considers the lesion to be of that particular kind.

- Deep convolutional networks are the state of the art in image classification and get better and better with more training data. So far we have tried AlexNet[8], GoogleNet[11] and are currently experimenting with ResNet[5]. If time permits we want to try out Net2Net [2] which provides an efficient way to transfer knowledge from one neural network to another.

4 Users

The tool can be used by dermatologists and patients.

5 Impact

The tool provides a low cost, scalable approach to detect skin cancer early by empowering patients and dermatologists and providing efficient and timely detection. We are in talks with a couple of dermatologists and would incorporate their feedback in our design. Further, we will be using cross validation to measure the accurancy of our neural networks.

If we are successful, we could reduce the thousands of death tolls to skin cancer each year. We also plan to host the website public and do beta testing by giving access to selective patients and health professionals.

6   Risks and Payoffs

- Uneasiness of adoption by dermatologists because of re-imbursement structure in healthcare. Dermatologists get paid every time a patient walks in to their office.

- Dermatologists also do not want to use more technology as they are already saturated with technologies.

- Cold start problem: Lack of training data for a few classes initially, might cause the network to have bad classification accuracy for a few classes. This might lead to dermatologists losing trust in the system.

7   Costs and Timeline

The overall approach is very cost-effective. We rely completey on open source technologies like tensorflow[1] and caffee[6] for our building and training deep neural network. We use Ruby on Rails for building the web application which is also open source.Typical training and fine-tuning of parameters for the model would require 100 hours of training time. Amazon dedicated GPU instance typically cost $0.65/hour

- Explore and experiment various convolutional neural network models (1-2 months)

- Build the web application (1-2 months). We plan to do these two steps in parallel

- Final report and evaluation and gathering feedback. (2 weeks)

8   Evaluation and Checkpoints

1. We aim to achieve an accuracy of 90% for the binary classification case.

2. Build an end to end web application with user and clinician interfaces.

3. Build a service which can compute score for each uploaded image

The tasks are split as follows among the team members. Stefano is mainly focussing on training the deep network. Thanh will be focussing on building the UI and visualization component. Matthew will be focussing on the web application and Apurv would be focussing on data pre-processing and integrating the components.

References

[1] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke,

V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. Software available from tensorflow.org.

[2] T. Chen, I. J. Goodfellow, and J. Shlens. Net2net: Accelerating learning via knowledge transfer. *CoRR*, abs/1511.05641, 2015.

[3] A. Esteva, B. Kuprel, and S. Thrun. Deep networks for early stage skin disease and skin cancer classification. Unpublished manuscript, 2015.

[4] M. Gniadecka, P. A. Philipsen, S. Wessel, R. Gniadecki, H. C. Wulf, S. Sigurdsson, O. F. Nielsen, D. H. Christensen, J. Hercogova, K. Rossen, H. K. Thomsen, and L. K. Hansen. Melanoma diagnosis by raman spectroscopy and neural networks: Structure alterations in proteins and lipids in intact cancer tissue. *Journal of Investigative Dermatology*, 122(2):443 – 449, 2004.

[5] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015.

[6] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. *arXiv preprint arXiv:1408.5093*, 2014.

[7] M. Kreutz, M. Anschütz, S. Gehlen, T. Grünendick, and K. Hoffmann. *Bildverarbeitung für die Medizin 2001: Algorithmen — Systeme — Anwendungen*, chapter Automated Diagnosis of Skin Cancer Using Digital Image Processing and Mixture-of-Experts, pages 357–361. Springer Berlin Heidelberg, Berlin, Heidelberg, 2001.

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.

[9] H. Lee and Y. P. Chen. Image based computer aided diagnosis system for cancer detection. *Expert Syst. Appl.*, 42(12):5356–5365, 2015.

[10] M. A. Sheha, M. S. Mabrouk, and A. Sharawy. Automatic detection of melanoma skin cancer using texture analysis.

[11] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *CVPR 2015*, 2015.

[12] J. Zhao, H. Zeng, D. McLean, S. Kalia, and H. Lui. Recent advances in real-time raman spectroscopy for in vivo skin cancerdiagnosis. In *Optics in the Life Sciences*, page BT4A.6. Optical Society of America, 2015.