Malaria detection in Segmented Blood Cell using Convolutional Neural Networks and Canny Edge Detection

Tahsinur Rahman Talukdar1,*, Mohammad Jaber Hossain1, Tahmid H. Talukdar2
1Department of Computer Science and Engineering, Leading University, Sylhet, Bangladesh.
2Holcombe Department of Electrical and Computer Engineering, Clemson University, USA
*corresponding author. email: tahsinurrahmantalukdar@gmail.com

Abstract: We apply convolutional neural networks to identify between malaria infected and non-infected segmented cells from the thin blood smear slide images. We optimize our model to find over 95% accuracy in malaria cell detection. We also apply Canny image processing to reduce training file size while maintaining comparable accuracy (~ 94%).

Introduction

Conventional optimal methods of infection diagnosis required sluggish, laborious, costly, and professional expertise. Automated diagnosis solutions provide an economical, swift, efficient, and accurate alternative. Computer vision based change detection is useful for various number of applications in multiple sectors [1]. Medical imaging is an influential advance in the field of medicine [2]. Especially, digital image processing for medical applications is an emerging topic of interest [3]. An automated process for microbiological identification is an optimistic solution for reducing analysis time and reduce workload on medical personnel [4]. Machine learning and neural networks can have a strong impact in alleviating these workloads. It has already shown success in some medical fields [5]. Neural networks are becoming more popular in use as they are more frequently being applied for pattern recognition and classification in images [6].

Image classification is important for computer vision which has significance in our everyday life [7]. In particular, facial recognition is currently ubiquitous thanks to widespread use of social media [8]. Inspiration for convolutional neural networks (CNN) comes from the mammalian visual system structure [9]. CNNs are gaining more wide-spread use in phones which can lead to large commercial application in the medical field [10]. It is domineering the field of machine learning approach for visual object recognition [11]. CNN as a machine learning algorithm is a fast classifier of big data as well as accurate predictor of disease[12]. It has revolutionized pattern recognition of images which includes medical images [13].

In general, CNNs have deeper layers and are arranged in a volumetric fashion with height, width as well as depth [14]. It has shown great results in computer vision tasks[15]. CNNs is a popular machine learning algorithm not only in the computer vision community but also natural language processing to hyperspectral image processing [16], [17] and to medical image analysis [18].
**Methodology**

Our dataset is provided by National Institute of Health (NIH). It is a repository containing thin blood smear slide images from the *Malaria Screener* research activity [19]. Giemsa-stained thin blood smear slides were collected from 150 infected and 50 healthy patients in Chittagong Medical College Hospital, Bangladesh. The images are captured using a smartphone camera in the microscopic view. Images were classified manually by an expert slide reader at Mahidol-Oxford Tropical Medicine Research Unit in Bangkok, Thailand. The dataset contains a total of 27,558 cell images with equal amounts of infected and un-infected cells [19].

We separate the images in two folders and train our convolutional neural networks to classify them. As illustrated in Fig. 1, our CNN has 4 parts: (1) Convolution layer, (2) Pooling Layer, (3) Normal Layer, and (4) Dropout layer.

Example input images are shown in Figure 2. There is a clear difference when observed manually which we expect the neural networks to pick up fairly accurately. Our convolution layer inputs the images based on the sizes sent to the image (64x64 in this case). A 3x3 kernel filter is applied to the original 64x64 image. The Pooling layer to be a more specific max-pooling layer picks the maximum number in each patch in the feature map in the matrix. In this case, the max pool feature map is (2x2).
Batch normalization makes each mini-pact ready for the inputs to a layer for which steadies the learning process and minimizes the number of training epochs needed to train neural networks. Dropout means dropping neurons randomly in the neural network to prevent overfitting. At first the efficiency was 80%. After adding more layers, the efficiency increases to 85-90%. After further epoch increase to 95%. Drawback being that increased as well. An extra layer being flattening layer that creates a long line of input data in vector form for the neural network.

Our CNN includes a hidden layer which consists of 3 parts: (1) Hidden Layer, (2) Normal layer, and (3) Dropout layer. The dense layer contains interconnected 512 neurons. The entire three parts make up 1 entire Hidden Layer. We implemented 4 CNN and 4 Hidden Layer networks.

Now at the end of processing activation function determines the result. We implemented a sigmoid function here. However, “tanh” and “relu” show similar classification performances. Adam optimizer is used because its common and training cost effective. Categorical cross-entropy is common. We find maximum accuracy is reached around epoch is 4-5. Further increase in number of epochs results in higher training time but without any increase in accuracy. Lower number of epochs are also preferable to avoid overfitting. We find that the best approach is to keep an epoch which minimizes training time and maximizes tested accuracy. This process will be repeated until the accuracy of the process reaches its optimal state.

We further processed images via Canny edge detection and removed RGB colors only left edges which reduced size for better memory utilization in database centers. Removing colors slightly reduce the accuracy to 94%. Training time remains constant regardless. Altered images have 1/3rd the size of the original. Canny edge detection has lower granules so the possibilities for false positive results are lower that’s why this edge detection method was prioritized. Example image where Canny edge detection is applied is shown in Figure 4.
Figure 4. Default vs Canny edge detection algorithm and output image

Image edge contains internal information like direction, characteristics, shape etc, and its also widely used in image segmentation, categorization, registration, and pattern recognition [20]. Edge detection is an efficient and effective processing tool of images which provides necessary information and characteristics for those images [21]. Medical images edge detection is important for object recognition of the human organs [22]. Data classification in presence of noise leads to less accurate results [23]. Optimized and skillfully designed CNNs have potential to provide a better performance in the future [24].

Results:
Results are illustrated in Table 1.

| Table 1. Results |
|-------------------|
| **Raw** | **CANNY** |
| **Accuracy (Test1, Test2, Test3)** | 95.43% | 94.52% |
| 95.88% | 94.78% |
| 95.45% | 94.36% |
| **Training Time (in seconds)** | 584s | 586s |
| 572s | 578s |
| 573s | 594s |
| **Image Size(in Megabytes)** | 334 MB | 139 MB |
| **Epoch number** | 5 |
| **Image Numbers** | 27558 Images |
| **System** | Intel(R) Core i7, 12 GB |

**Accuracy**
Average accuracy: 95%
Canny Edge Detection accuracy: 94%

**Data size**
Default Data Size: 334 MB.
Canny Edge Detection Data Size: 139 MB. (1/3rd of Default Data Size)
Training time
Default Training Time: 9-10 Minutes
Canny Edge Detection Training Time: 9-10 Minutes

Improvements in accuracy can be made by using more images in datasets.

Conclusion
In conclusion, we demonstrate a convolutional neural network classifier that is able to identify malaria infected cells from microscope slide images with near 95% accuracy with a training time of less than 10 minutes. We believe this would enable a smartphone based automated process of fast and efficient diagnosis while reducing the workload of healthcare workers. This can impact the way we diagnose and detect and store data for viruses in the future.

References

[1] R. J. Radke, S. Andra, O. Al-Kofahi, and B. Roysam, “Image change detection algorithms: a systematic survey,” IEEE Trans. Image Process., vol. 14, no. 3, pp. 294–307, Mar. 2005, doi: 10.1109/TIP.2004.838698.

[2] K. H. Jin, M. T. McCann, E. Froustey, and M. Unser, “Deep Convolutional Neural Network for Inverse Problems in Imaging,” IEEE Trans. Image Process., vol. 26, no. 9, pp. 4509–4522, Sep. 2017, doi: 10.1109/TIP.2017.2713099.

[3] Z. Stosic and P. Rutesic, “An Improved Canny Edge Detection Algorithm for Detecting Brain Tumors in MRI Images,” vol. 3, p. 5, 2018.

[4] T. Treebupachatsakul and S. Poomrittigul, “Bacteria Classification using Image Processing and Deep learning,” in 2019 34th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC), JeJu, Korea (South), Jun. 2019, pp. 1–3. doi: 10.1109/ITC-CSCC.2019.8793320.

[5] J. Ker, L. Wang, J. Rao, and T. Lim, “Deep Learning Applications in Medical Image Analysis,” IEEE Access, vol. 6, pp. 9375–9389, 2018, doi: 10.1109/ACCESS.2017.2788044.

[6] G. Jakimovski and D. Dacev, “Lung cancer medical image recognition using Deep Neural Networks,” in 2018 Thirteenth International Conference on Digital Information Management (ICDIM), Berlin, Germany, Sep. 2018, pp. 1–5. doi: 10.1109/ICDIM.2018.8847136.

[7] T. Guo, J. Dong, H. Li, and Y. Gao, “Simple convolutional neural network on image classification,” in 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA), Beijing, China, Mar. 2017, pp. 721–724. doi: 10.1109/ICBDA.2017.8078730.

[8] J. Wu and Z.-H. Zhou, “Face recognition with one training image per person,” Pattern Recognit. Lett., vol. 23, no. 14, pp. 1711–1719, Dec. 2002, doi: 10.1016/S0167-8655(02)00134-4.

[9] Y. LeCun, L. Bottou, Y. Bengio, and P. Ha, “Gradient-Based Learning Applied to Document Recognition,” p. 46, 1998.

[10] X. Lin, C. Zhao, and W. Pan, “Towards Accurate Binary Convolutional Neural Network,” ArXiv171111294 Cs Stat, Nov. 2017, Accessed: Feb. 21, 2022. [Online]. Available: http://arxiv.org/abs/1711.11294
[11] G. Huang, Z. Liu, G. Pleiss, L. Van Der Maaten, and K. Weinberger, “Convolutional Networks with Dense Connectivity,” *IEEE Trans. Pattern Anal. Mach. Intell.*, pp. 1–1, 2019, doi: 10.1109/TPAMI.2019.2918284.

[12] D. Dahiwade, G. Patle, and E. Meshram, “Designing Disease Prediction Model Using Machine Learning Approach,” in *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, Mar. 2019, pp. 1211–1215. doi: 10.1109/ICCMC.2019.8819782.

[13] S. Kido, Y. Hirano, and N. Hashimoto, “Detection and classification of lung abnormalities by use of convolutional neural network (CNN) and regions with CNN features (R-CNN),” in *2018 International Workshop on Advanced Image Technology (IWAIT)*, Chiang Mai, Jan. 2018, pp. 1–4. doi: 10.1109/IWAIT.2018.8369798.

[14] R. L. Galvez, A. A. Bandala, E. P. Dadios, R. R. P. Vicerra, and J. M. Z. Maningo, “Object Detection Using Convolutional Neural Networks,” in *TENCON 2018 - 2018 IEEE Region 10 Conference*, Jeju, Korea (South), Oct. 2018, pp. 2023–2027. doi: 10.1109/TENCON.2018.8650517.

[15] Ming Liang and Xiaolin Hu, “Recurrent convolutional neural network for object recognition,” in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, USA, Jun. 2015, pp. 3367–3375. doi: 10.1109/CVPR.2015.7298958.

[16] N. Tajbakhsh et al., “Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?,” *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1299–1312, May 2016, doi: 10.1109/TMI.2016.2535302.

[17] S. Rajaraman et al., “Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images,” *PeerJ*, vol. 6, p. e4568, Apr. 2018, doi: 10.7717/peerj.4568.

[18] X. Wang and J.-Q. Jin, “An Edge Detection Algorithm Based on Improved CANNY Operator,” in *Seventh International Conference on Intelligent Systems Design and Applications (ISDA 2007)*, Rio de Janeiro, Brazil, Oct. 2007, pp. 623–628. doi: 10.1109/ISDA.2007.6.

[19] S. Agaian and A. Almuntashri, “Noise-resilient edge detection algorithm for brain MRI images,” in *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Minneapolis, MN, Sep. 2009, pp. 3689–3692. doi: 10.1109/IEMBS.2009.5334731.

[20] Y. Zhao, W. Gui, Z. Chen, J. Tang, and L. Li, “Medical Images Edge Detection Based on Mathematical Morphology,” p. 4.

[21] M. Koziarski and B. Cyganek, “Image recognition with deep neural networks in presence of noise – Dealing with and taking advantage of distortions,” *Integr. Comput.-Aided Eng.*, vol. 24, no. 4, pp. 337–349, Sep. 2017, doi: 10.3233/ICA-170551.

[22] G. Xu, H.-Z. Wu, and Y.-Q. Shi, “Structural Design of Convolutional Neural Networks for Steganalysis,” *IEEE Signal Process. Lett.*, vol. 23, no. 5, pp. 708–712, May 2016, doi: 10.1109/LSP.2016.2548421.