

# Behind the Pixels: An Empirical Study of Novel Machine Learning Preprocessing Techniques for Image Classification

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## I. INTRODUCTION

**C**ONVOLUTIONAL Neural Networks (CNNs) have revolutionized image classification tasks. It has many applications, such as automatically detecting street signs to reduce the number of tasks the driver needs to do while driving or detecting rust on steel that can compromise structural integrity. [1, 2]. However, CNN performance can be significantly impacted by the quality and characteristics of input images (i.e. training data). In this paper, we investigate the effects of various image preprocessing techniques on the accuracy of CNN models for image classification.

## II. LITERATURE REVIEW

### A. Background

There has been much effort put into constructing CNN models that aim to aid in the medical process of detecting various cancers. It has been shown that, among 12 breast cancer detecting models, the accuracies of those models range from 85.5% to 97.8% [3]. Other common cancers, such as brain cancer, likely have models with similar ranges of accuracies. With the hope of employing these models on a large scale to aid doctors, improving the accuracies of these cancer detecting models would allow them to be used with higher confidence and lower the possibility of misdiagnoses.

### B. Edge Detection

The first image preprocessing technique examined in this study is edge detection. The edge detection technique is a

computer algorithm that targets boundary information of objects in images by analyzing pixel mutations of images [4]. That is, the algorithm detects discontinuities of brightness in images and reflects the information gathered in a new image, as shown in Figure 1.

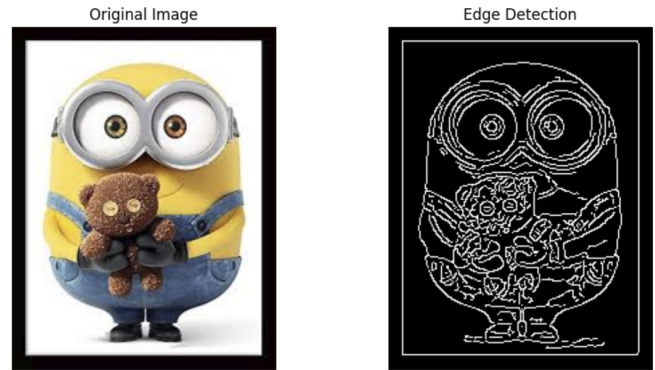


Fig. 1: A minion image before and after edge detection image processing

We have chosen the Canny edge detection algorithm due to its resistance to noise and random variations in color or brightness and is capable of detecting weak edges [5]. Since medical images are likely to contain very weak edges of body tissues and potentially noise, the Canny edge detection algorithm is appropriate for this task.

### C. Image Segmentation

The other image processing technique we will examine is the image segmentation technique. The image segmentation technique partitions an image into distinct regions or segments to simplify its analysis. This process groups pixels based on characteristics like color, intensity, or texture, making it

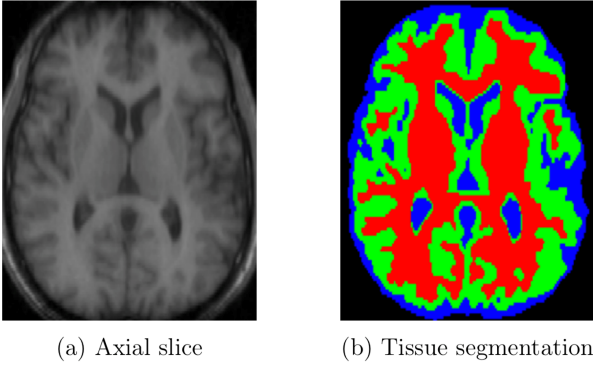


Fig. 2: A scan of a brain before and after image segmentation

easier to isolate specific objects or areas within an image [6]. As technology continues to advance, image segmentation is used in a wide spectrum of fields, ranging from object detection in autonomous cars to medical images processing [7, 8]. In medical imaging, segmentation helps identify tumors by distinguishing them from surrounding healthy tissues [9].

### III. METHODOLOGY

Kaggle is a data science platform that houses various data designated for the public to train machine learning models. We downloaded 10986 images of brain cancer from the Multi Cancer Dataset consisting of three subtypes: glioma, meningioma, and pituitary tumor. We stored these images in Google Drive. We utilized Google Colab for its integration with Google Drive and its cloud computing features, allowing us to run our model on enterprise level equipment in the cloud instead of locally on our machines.

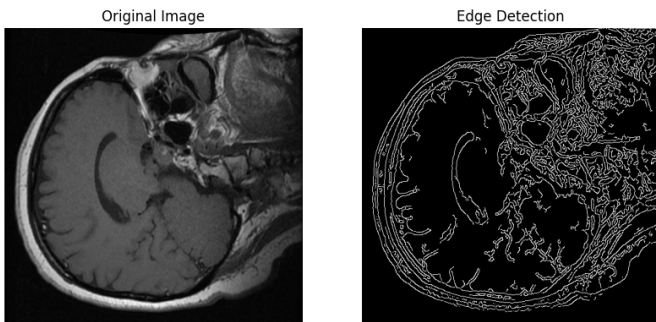


Fig. 3: A sample of medical image of brain tumor used in Google Colab machine learning training

Using the data, we developed the CNN model with the PyTorch library, allocating 8788 images for training. To prepare these images, we converted them to a tensor-readable format.

### IV. PRELIMINARY RESULTS

After inputting various parameters such as learning rate, batch size, and epochs, we acquired numerical data from the model.

Trial	Normal	Edge
1	0.4140	0.4718
2	0.4718	0.4413
3	0.4413	0.4631
4	0.3672	0.4413
5	0.4718	0.4413
Average	0.4332	0.4518

TABLE I: A table of overall CNN model accuracies where Learning Rate = 0.001, Batch Size = 64, and Epochs = 5.

While the accuracies are not as high as we hoped, this data does suggest that utilizing edge detection may improve CNN performance as it performed better than the normal model in this case. We will investigate the models more in-depth in the near future.

### V. CONCLUSION

Our research relates to the optimization of CNN-based image classification models. By investigating the effects of preprocessing techniques, such as edge detection and image segmentation, we aim to enhance the accuracy and reliability of these models. The use of the Canny edge detection algorithm, known for its resistance to noise and sensitivity to weak edges, holds promise for improving medical image analysis.

Our future work will focus on refining the preprocessing techniques and evaluating their impact on different CNN models. Additionally, we will explore the scalability of our proposed methods to other medical imaging applications.

## APPENDIX A

## WEBSITE

<https://behind-the-pixels.github.io/>

## REFERENCES

- [1] N. Jmour, S. Zayen, and A. Abdelkrim, "Convolutional neural networks for image classification," pp. 397–402, 2018. DOI: 10.1109/ASET.2018.8379889.
- [2] H. Lyu, "Research on corrosion recognition method of steel based on convolutional neural network," pp. 507–511, 2023. DOI: 10.1109/ICISCAE59047.2023.10393077.
- [3] K. Patel, S. Huang, A. Rashid, B. Varghese, and A. Gholamrezanezhad, "A narrative review of the use of artificial intelligence in breast, lung, and prostate cancer," *en, Life (Basel)*, vol. 13, no. 10, Oct. 2023.
- [4] R. Sun *et al.*, "Survey of image edge detection," *Frontiers in Signal Processing*, vol. 2, Mar. 2022. DOI: 10.3389/frsip.2022.826967.
- [5] B. Tian and W. Wei, "Research overview on edge detection algorithms based on deep learning and image fusion," *Security and Communication Networks*, vol. 2022, pp. 1–11, Sep. 2022. DOI: 10.1155/2022/1155814.
- [6] R. Anand, R. K. Mishra, and R. Khan, "Chapter 9 - plant diseases detection using artificial intelligence," M. A. Khan, R. Khan, and M. A. Ansari, Eds., pp. 173–190, 2022. DOI: <https://doi.org/10.1016/B978-0-323-90550-3.00007-2>. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/B9780323905503000072>.
- [7] B. De Brabandere, D. Neven, and L. Van Gool, "Semantic instance segmentation for autonomous driving," Jul. 2017.
- [8] I. Rizwan I Haque and J. Neubert, "Deep learning approaches to biomedical image segmentation," *Informatics in Medicine Unlocked*, vol. 18, p. 100297, 2020, ISSN: 2352-9148. DOI: <https://doi.org/10.1016/j.imu.2020.100297>. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S235291481930214X>.
- [9] D. Jha, M. A. Riegler, P. Halvorsen, and D. Johansen, "Medical image segmentation using deep learning," n.d. Accessed: 16 December 2024. [Online]. Available: [https://experiments.springernature.com/articles/10.1007/978-1-0716-3195-9\\_13](https://experiments.springernature.com/articles/10.1007/978-1-0716-3195-9_13).