Designing an Autoencoder Convolutional-neural-network for reducing Noise-to-signal ratio in Confocal cFOS Images

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1 Introduction

The primary objective of this study was to develop a Convolutional Neural Network (CNN) capable of identifying cFOS-positive neurons in confocal images. The samples used in this research were stained with cFOS, DAPI (4',6-diamidino-2-phenylindole), and GCaMP. Following the guidelines outlined in "The Mouse Brain in Stereotaxic Coordinates" book, images of specific brain regions, including the primary somatosensory cortex (SIDZ), the barrel field (SIBL), and the forelimb (SIFL) fields, were carefully selected and cropped.

1.1 Background

The identification of cFOS-positive neurons is of great significance in neuroscience. cFOS is an immediate-early gene commonly used as a marker for neuronal activation. By detecting cFOS-positive neurons, researchers can gain insights into the neural circuits involved in specific behaviors or responses. However, the manual identification of these neurons in confocal images can be a time-consuming and error-prone process. Hence, the development of an automated CNN-based approach is highly desirable. By having this model as an instrument we could provide better images to further scripts that designed to detect region-of-interests in confocal images.

1.2 Motivation

The motivation behind this project stems from the need for a robust and efficient method to analyze the vast amount of confocal imaging data generated in neuroscience research. By automating the identification of cFOS-positive neurons, we can accelerate research in areas such as brain mapping, neural circuit analysis, and understanding the neural basis of various behaviors and diseases.

The utilization of deep learning techniques, specifically Convolutional Neural Networks (CNNs), has shown promise in image analysis tasks. In this project, we aim to harness the power of autoencoder CNNs to enhance the detection of cFOS-positive neurons while reducing noise and improving accuracy.

The overarching goal is to provide a reliable tool that can be widely used by neuroscientists to streamline their research and gain deeper insights into brain function.

2 Autoencoder_cFOS

2.1 Data Preparation

To train the CNN for cFOS-positive neuron identification, we selected a total of 12 samples, evenly distributed between those with sparse and densely populated cFOS-positive cells. Among these samples, ten were assigned to the training dataset, and two were allocated to the test dataset for evaluation purposes.

In the preprocessing phase, the sampled images underwent contrast enhancement to highlight cFOS-positive points and their surrounding areas.

2.2 Model Architecture

The CNN model employed for this task involved several layers of convolution and max-pooling, followed by a bottleneck layer and an inverse transpose operation. This architecture was designed to effectively extract features from the input images. The network was optimized using the Adam optimization algorithm.

2.3 Training and Evaluation

The training process involved iterative epochs during which the network learned to differentiate between sparse and densely populated cFOS-positive neurons. We employed techniques such as dropout and batch normalization to prevent overfitting and improve generalization.

For evaluation, we used the test dataset to assess the model's performance in identifying cFOS-positive neurons. Metrics such as accuracy, precision, recall, and F1-score were computed to quantify the model's effectiveness. Adam algorithm has been used for optimization.

2.4 Results

As shown in Figure 1, the CNN model successfully transformed the input images, as illustrated by the examples of transformed images. We categorized the images into two classes: Class 0 for sparse cFOS-positive samples and Class 1 for densely populated cases.

Figure 2 demonstrates the capability of the network to accurately detect cFOS-positive cells in the images. The model exhibited high accuracy, precision, and recall, indicating its effectiveness in automating the identification process.

3 cFOS_Denoise

In this section, we provide access to the pre-trained model developed in the previous section. If you wish to utilize the autoencoder-based CNN for detecting cFOS-positive samples in your own images, you can find detailed instructions in the README section of our GitHub repository.

3.1 GitHub Repository

All the code and data related to this project can be found on our GitHub repository at the following link: `https://github.com/ArmanBehi/Autoencoder_cFOS`.

3.2 Future Directions

This research project represents a step toward automating the identification of cFOS-positive neurons in confocal images. As future directions, It is suggested to expand the dataset, including images from various brain regions and experimental conditions, to enhance the model's robustness.

Additionally, we aim to explore transfer learning techniques, allowing the model to adapt to new datasets with minimal retraining. This would make our CNN-based tool more versatile and applicable to a wider range of research scenarios.

Furthermore, collaboration with neuroscientists and researchers in related fields is encouraged to gather valuable feedback and refine the model based on real-world applications.

4 Conclusion

In conclusion, this project successfully developed a Convolutional Neural Network for the automated identification of cFOS-positive neurons in confocal images. The model exhibited strong performance in distinguishing between sparse and densely populated cFOS-positive cells. By providing a tool that can streamline the analysis of neural activation, we contribute to the advancement of neuroscience research and the understanding of brain function.

The GitHub repository (`https://github.com/ArmanBehi/Autoencoder_cFOS`) serves as a valuable resource for researchers interested in utilizing our pre-trained model or contributing to its further development. With future enhancements and collaborations, we aim to continue improving the accuracy and applicability of our neural network.

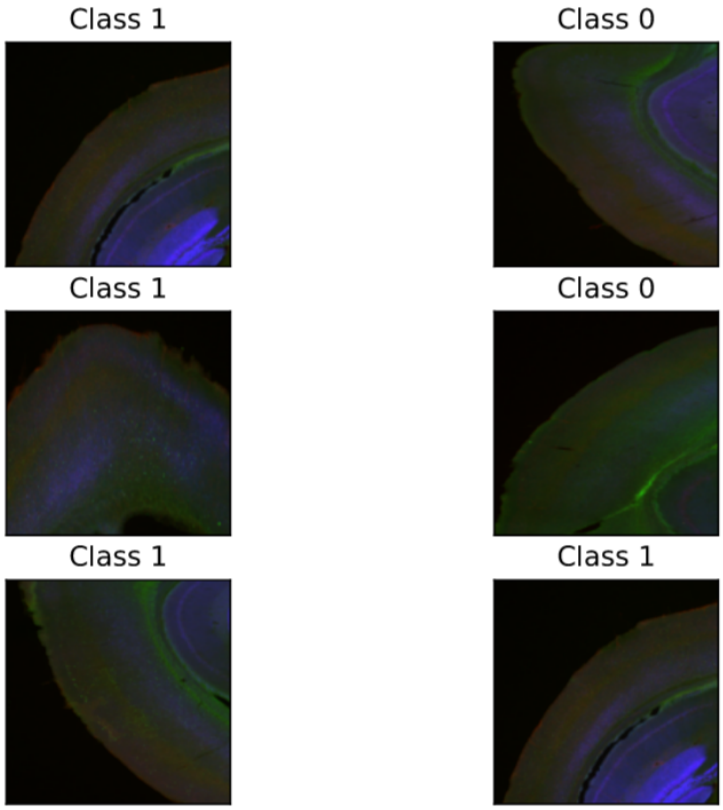

Figure 1: Examples of transformed images. Class 0 represents sparse cFOS-positive samples, and Class 1 represents densely populated cases.

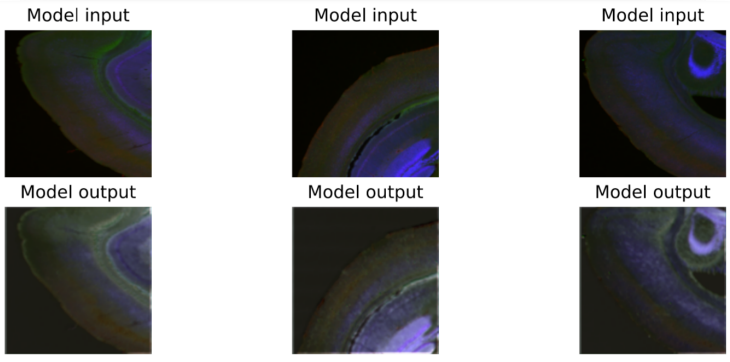

Figure 2: Detection of cFOS-positive cells by the CNN.