cell detection for various cell shapes

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1 Introduction

Recent cell detection methods using CNN achieved good performance. However, those learning-based methods basically require training data for each condition(e.g., cell types, culture conditions, density).

It is important for users(biologists) to know how a network works on the images with a different condition, and how much annotation data is additionally required to train it for different conditions.

In this study, we investigate the relationship between the accuracy of detection networks with different conditions and the number of training data. This analysis is also important for developing the semi-supervised detection method that is our future work.

2 Cell detection

We use a U-Net[1] as a CNN model for detecting cell position. To train the U-Net from the input of the original image, we use the mean of the squared error loss function (MSE) between the estimated image and the ground-truth likelihood map[2]. The ground-truth likelihood map represents a cell position with a Gaussian distribution.

3 Experiments

3.1 Culture condition and dataset

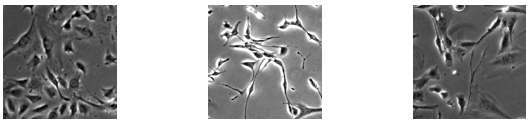
Cell differentiation proceeds depending on the culture conditions, and the cell shapes change. To investigate the relationship between the accuracy of detection networks with different culture conditions, these experiments were conducted on datasets that C2C12 myoblast cells were cultured under three culture conditions; 1)FGF2(fibroblast growth factor), 2)BMP2(bone morphogenetic protein), 3)FGF2+BMP2; both growth factor were added.

Here, the FGF2+BMP2 dataset has a wider variety of cell shapes than the other two dataset. Figure 1 shows examples of typical cell shapes corresponding to each culture condition.

3.2 Relationship between the amount of training data and culture condition

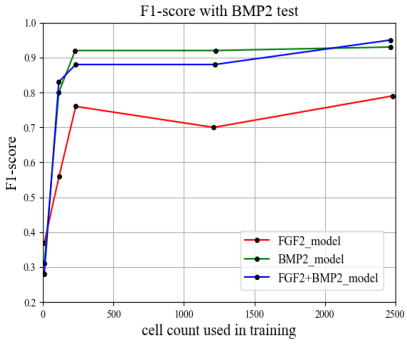
We conducted the following two steps in experiments. First, we trained three U-Net networks using three datasets under different culture conditions. Second, in each network, the accuracy of detection for each condition was investigated while changing the number of training data. In this experiment, the accuracy of detection was measured using F1-score.

Figure 2 shows these results where the horizontal axis is the number of cells in training data, and the vertical axis is the F1-score. The FGF2+BMP2 model, the expert which learned cells with various shapes, showed good performance for all cells. Besides, from the result that the FGF2 model showed weak performance against the BMP2 test, it could be seen that the performance of



(a) BMP2 (b) FGF2 (c) FGF2+BMP2

Figure 1: Examples of cell appearances under three different culture conditions.



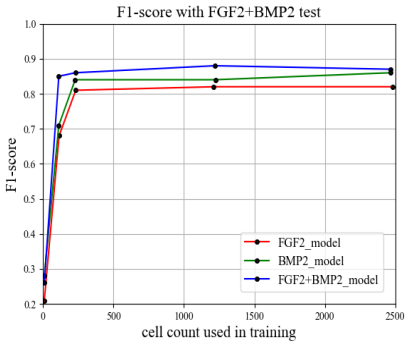


Figure 2: F1-score of three experts with BMP2test, FGF2+BMP2test.

cell detection changes according to the cell shapes. Interestingly, the experts showed relatively low performance but capable of detecting cells even though they learned only about 100 cells, the second-lowest number of cells in this experiment.

4 Conclusion

In this paper, we analyzed the relationship between the accuracy of detection networks with the number of training data and different culture conditions. As a result, it is possible to confirm the extension to the semi-supervised detection method.

Acknowledgement

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References

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