DEVELOPING AUTOMATED ROTIFER *Brachionus spp.* COUNTING METHOD USING BACKGROUND SUBTRACTION AND CONNECTED COMPONENTS ANALYSIS

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Abstract

Rotifers *Brachionus spp.* are a crucial starting diet for fish aquaculture. In commercial scale rotifer production, sampling and counting are essential for examining the rotifer population. Counting rotifer samples is usually manually executed by aquaculturists and is extremely time consuming and inefficient. Automated rotifer counting system would improve the production efficiency and release aquaculturists from the tedious work. The present study developed a computer vision model that can detect and count rotifers using background subtraction algorithm and recognize egg-carrying rotifers and non-egg-carrying rotifers using convolutional neural networks (CNN). The model achieved an average error rate of 4.09±3.08% for counting rotifers and an error rate of 9.46% for rotifer classification.

Keywords: rotifer, artificial intelligence, deep learning

Introduction

A typical rotifer culture pipeline can be dissected into a two stage process (Fig. 1) which needs live feed experts' labor and knowledge as input. The rotifer density and fertilization rate are the key indexes for rotifer culture management since the feeding rate and water exchange are decided based on these two indexes in common practice.

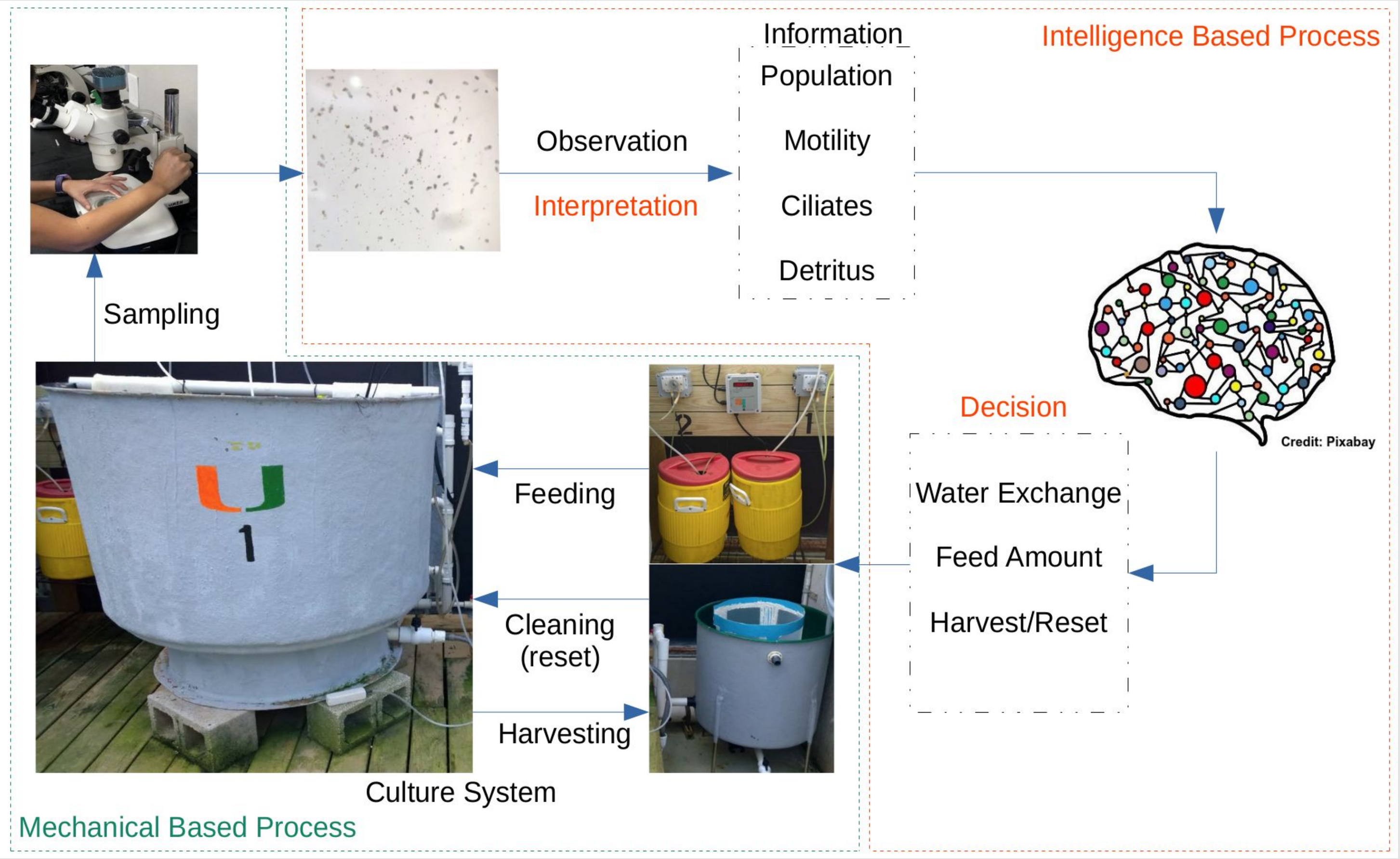

Figure 1. Rotifer Culture Pipeline

The purpose of this study is to develop a computer vision model that can analyze microscopic images of live rotifer samples, count the rotifers and recognize fertilized rotifers and unfertilized rotifers.

The Rotifer Dataset

The rotifer dataset consists of annotated microscopic (Leica GZ6 10x) videos of 0.1ml live rotifer samples and labeled object patches (Fig. 2). The video data were collected with iPhone 7 and microscope adapter (iDu LabCam). Each video was annotated with the Lugol-fixed count of rotifers. The object patches were generated via background subtraction algorithm. Each object patch was labeled as NECR (non-egg-carrying rotifer), ECR (egg-carrying rotifer), Null (negative detection), or Multi (multiple overlapped rotifers) by the live feed specialists at the University of Miami Experimental Hatchery.

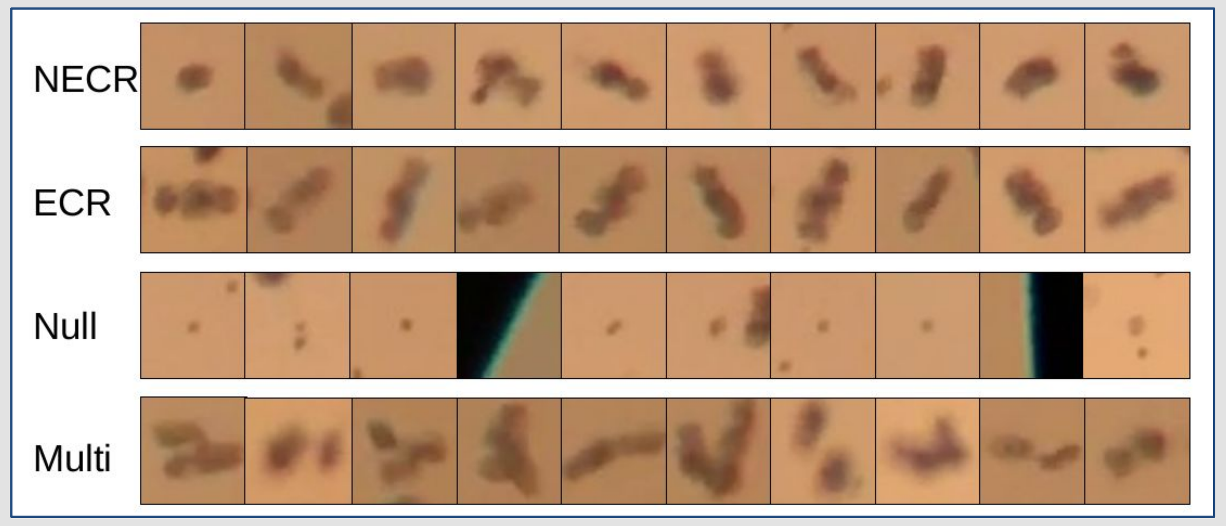

Figure 2. Labeled Object Patches

Pipeline

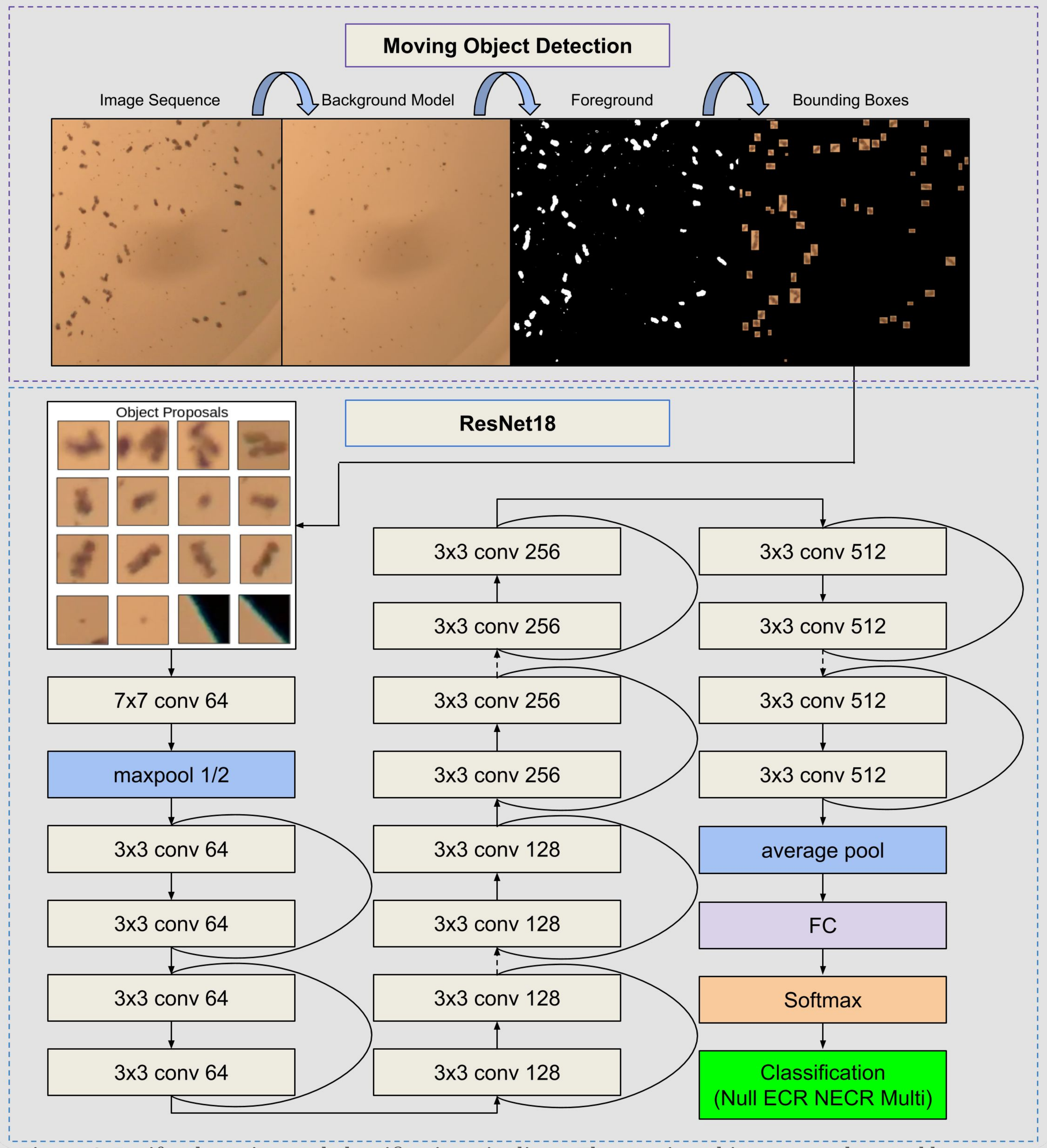

Figure 3. Rotifer detection and classification pipelines. The moving objects were detected by background subtraction algorithm. Then the object proposals were classified by a deep convolutional neural networks (ResNet18) trained on 2400 labeled object patches.

Results

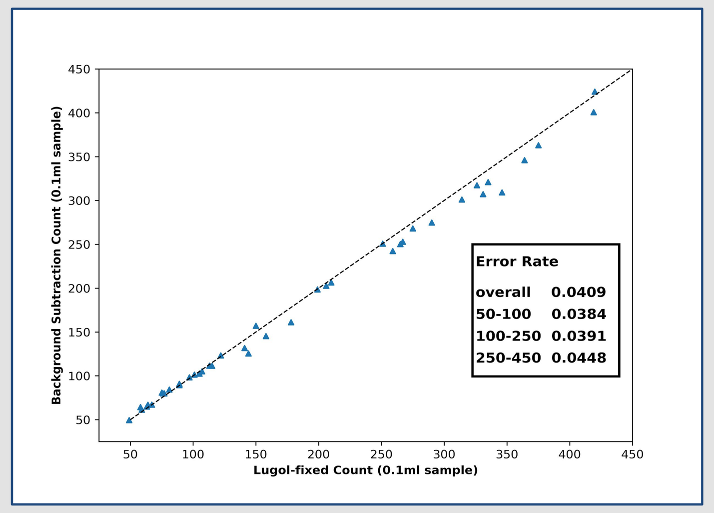

Figure 4. Rotifer count using background subtraction algorithm vs Lugol-fixed count. Diagonal dashed line is y=x.

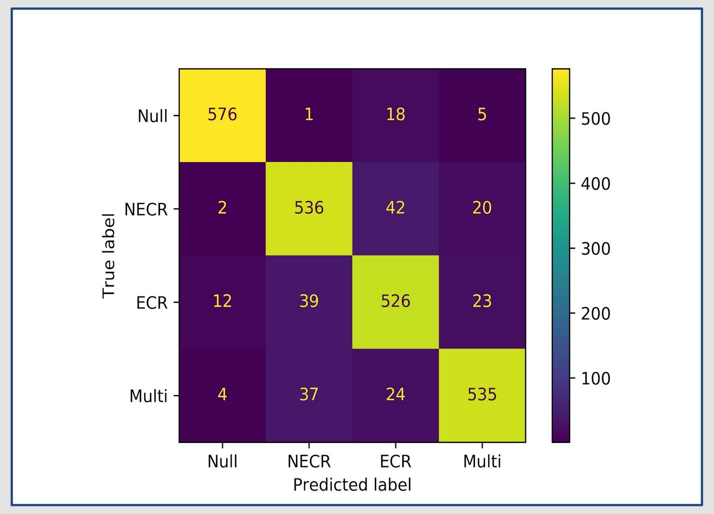

Figure 5. The classification model (ResNet18) was evaluated via 5-folds cross validation. A confusion matrix is used to investigate the performance. The overall classification accuracy is 90.54%.

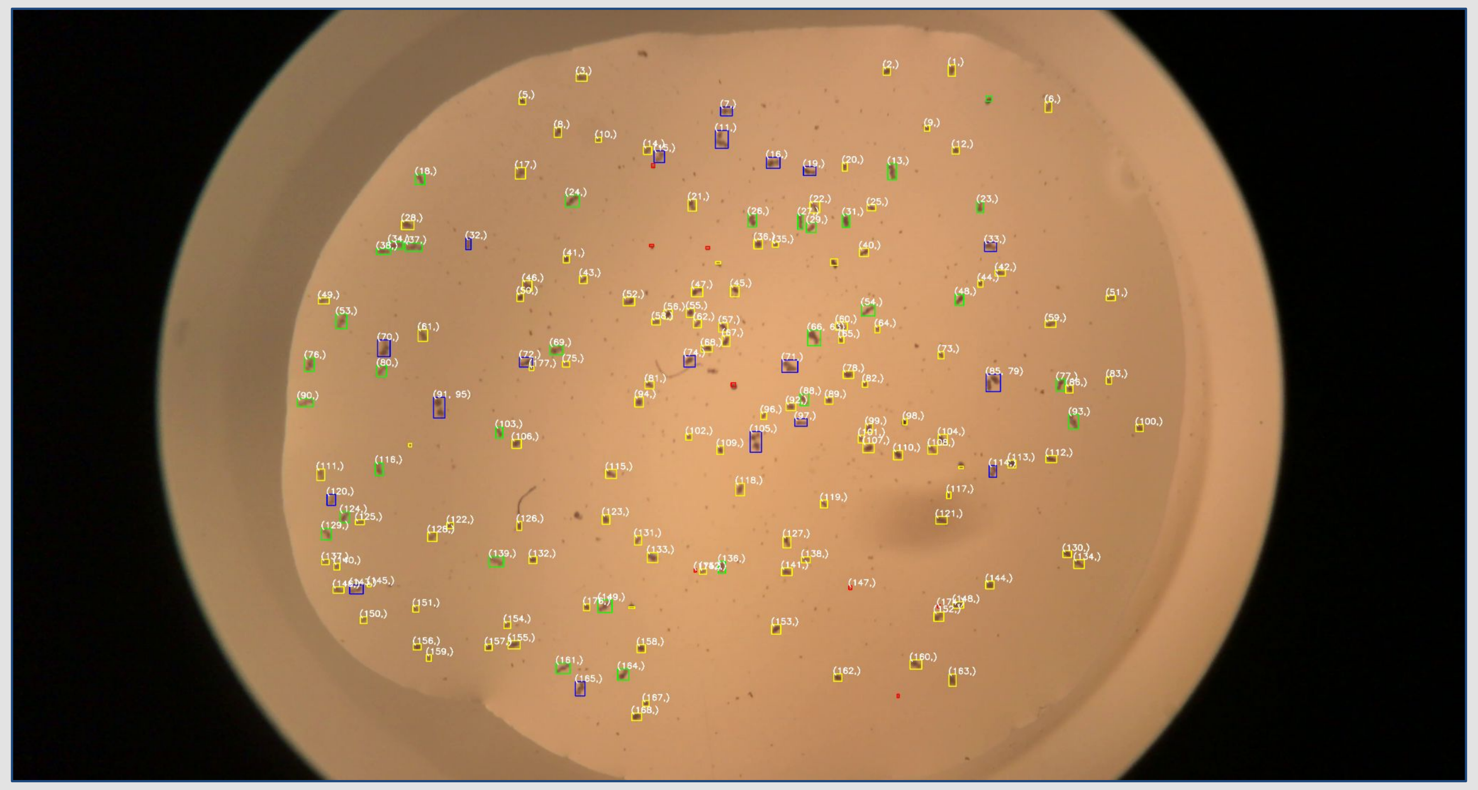

Figure 6. Rotifer detection and classification (Green: ECR; Yellow: NECR; Blue: Multi; Red: Null)

Future Work

- Investigate deeper models, different model architectures and optimization settings to achieve better classification accuracy.
- Develop tracking algorithms to track the classification history of each detected rotifer for better estimation of fertilization rate.
- Develop a deep learning model to evaluate the contamination level of the rotifer culture.

Acknowledgements

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