Artificial Neural Network-Based Cell Counter

Brendan Winn, Alan Cabrera, Amber Beserra, Michael Ginsberg, William Wells, Dr. Kevin Desai, PhD

The University of Texas at San Antonio, San Antonio, TX 78249

ABSTRACT

One important source of data in the natural sciences is microscope images. While analysis of these images is often complex, cell counting is one common task that would greatly benefit from automation. Many networks have been created for this purpose [1,2,4,5,6]. With this project, we seek to implement several artificial neural network architectures to evaluate their performance on cell counting in microscopic images. To do this, the networks were recreated in Python, then trained and evaluated on images from BBBC005 [3]. Our results suggest that the complexity of these models greatly increases the required training for the data to be appropriately learned.

INTRODUCTION

Cell counting is the process of enumerating each cell in a given image. This is a common task, frequently used to estimate the health status of the cells under examination. While relatively simple, complications arise as the number of cells increase, cell shapes overlap, and blur hinder cell recognition.

Artificial neural networks show promising results in this area. Many different network architectures have been devised and augmented to solve different issues with cell counting. Here, we select several network architectures to evaluate effectiveness at both in-focus and blurred images on different sizes of training sets.

OBJECTIVE

We seek to implement, train, and evaluate several different neural network architectures for cell counting against different conditions of blur and training set size.

HYPOTHESIS

While older architectures may provide better results with smaller training sets, the newer architectures will provide better results given a larger training set.

Additionally, models with higher parameter numbers will take longer to converge, and be more likely to overfit.

METHODOLOGY

Neural network architectures are modelled in Python's TensorFlow library. The following models are implemented:

- Convolutional Neural Network (CNN)
- Fully Convolutional Regression Network (FCRN) [4]
- Neural Arithmetic Logic Units-Augmented FCRN (NALU-FCRN) [4]
- Residual Neural Network (ResNet) [2]
- Fully Convolutional Network for Image Segmentation (U-Net)[5]
- Visual Geometry Group's Very Deep Convolutional Network (VGGNet) [6]
- Fully Convolutional Redundant Counting (Count-Ception) [1]

Each network will be trained under four different conditions:

1. Low number of training samples, no blur in samples
2. Low number of training samples, random blur in samples
3. High number of training samples, no blur in samples
4. High number of training samples, random blur in samples

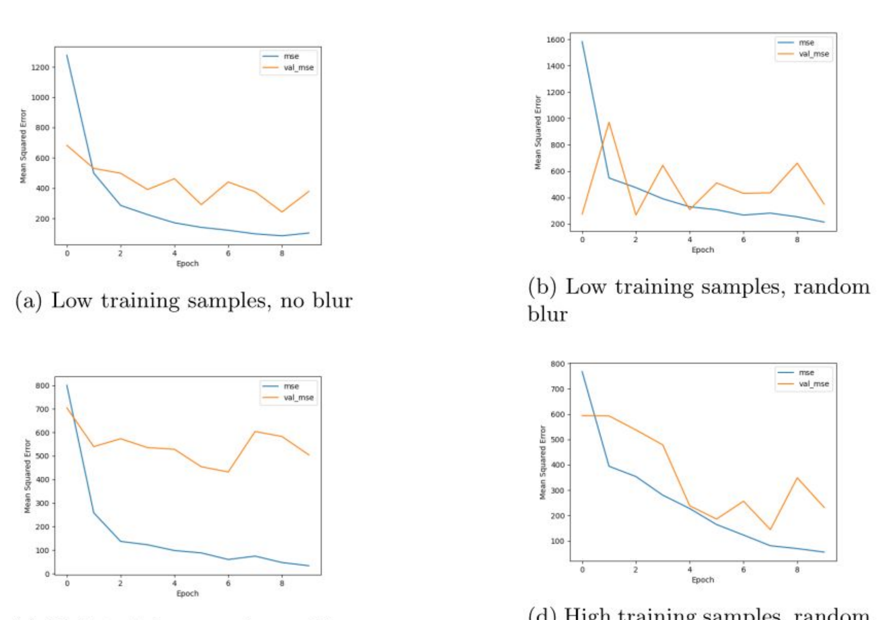
They will then be tested against 50 images with no blur, and 50 images with a random amount of blur.

RESULTS

Models are evaluated on the mean squared error (MSE) between predicted count and actual count. The models exhibited two distinct learning and validation curves, which are depicted below. In particular, the CNN model exhibited the most expected behavior (below-left): a decreasing training curve with a validation curve nearby.

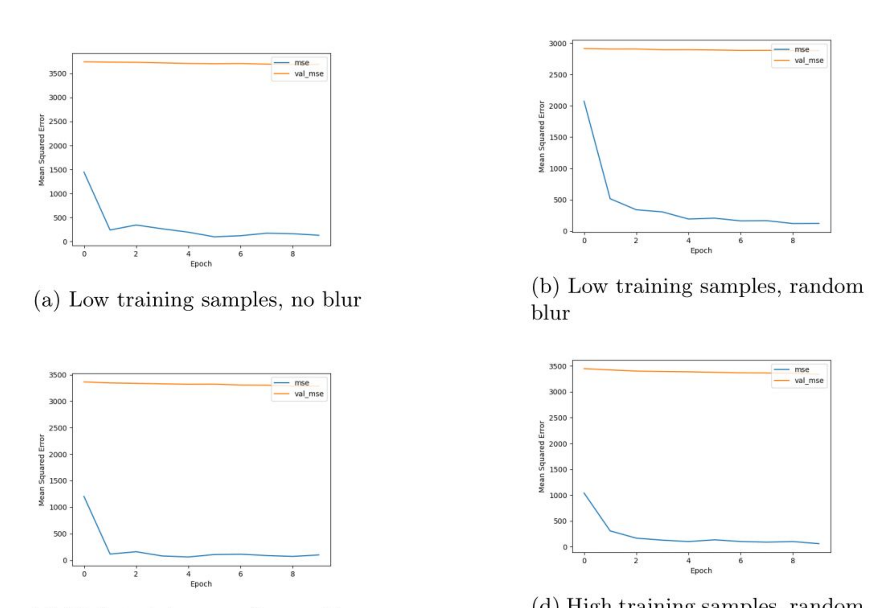
The other models all exhibit curves similar to the curves of NALU-FCRN (below-right). The training curves are as expected, with a fairly rapid decrease in the training MSE. The validation curves, however, remain high loss regardless of the training condition. This suggests that the other models are not learning the underlying structure, but instead are simply learning the data.

Testing data reflects this, with both non-blurred and randomly blurred images having a large loss.



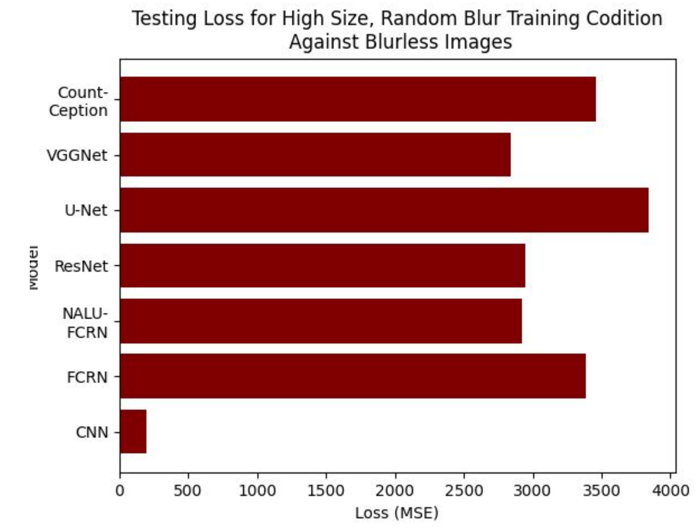
(a) Low training samples, no blur
(b) Low training samples, random blur
(c) High training samples, no blur
(d) High training samples, random blur

Figure: Graphs of training and validation curves for CNN training.

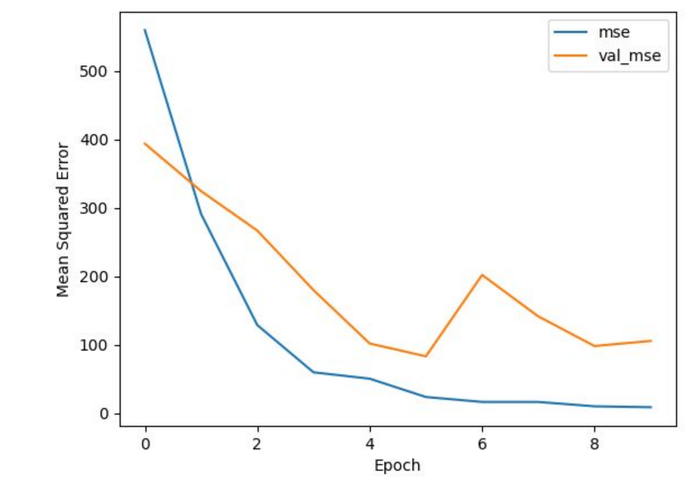


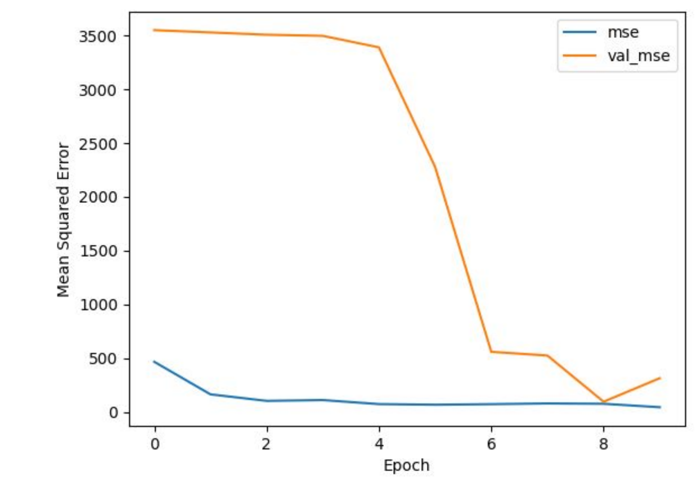
(a) Low training samples, no blur
(b) Low training samples, random blur
(c) High training samples, no blur
(d) High training samples, random blur

Figure: Graphs of training and validation curves for NALU-FCRN training.



An example of the testing loss for a particular condition is given in the figure to the left. The structure is similar for all other conditions: CNN with the lowest loss and all other models hovering about 3000 MSE.





To examine the possibility that the models were simply failing to learn, we compared the CNN model (left) against the NALU-FCRN model (right) at 2500 training samples. The results suggest that it is indeed the case that the models were failing to learn, and simply needed additional training.

SUMMARY

- ❖ For smaller training sizes, the simple CNN model outperforms all more complex models.
- ❖ The more complex models exhibit typical training curves, but have validation curves that start and remain high loss.
- ❖ Testing against individual images (both random and without blur) confirm that the complex models failed to learn.
- ❖ Follow up with some models showed that the issue is most likely a simple mismatch between the amount of training, and the model's complexity.
- ❖ Computational restrictions have prevented further testing at larger training sizes. Possible future work would be to examine models over an entire range of training data.

REFERENCES

[1] Cohen, Joseph & Lo, Henry & Bengio, Y.. (2017). Count-ception: Counting by Fully Convolutional Redundant Counting.
[2] He, Kaiming; Zhang, Xiangyu; Ren, Shaoqing; Sun, Jian (2016). Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Las Vegas, NV, USA: IEEE. pp. 770–778. arXiv:1512.03385. doi:10.1109/CVPR.2016.90. ISBN 978-1-4673-8851-1.
[3] Ljosa, Vebjorn & Sokolnicki, Katherine & Carpenter, Anne. (2012). Annotated high-throughput microscopy image sets for validation. Nature methods. 9. 637. 10.1038/nmeth.2083.
[4] Rana, Ashish & Singh, Taranveer & Singh, Harpreet & Kumar, Neeraj & Rana, Prashant. (2020). Exploring Cell counting with Neural Arithmetic Logic Units.
[5] Ronneberger O, Fischer P, Brox T (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. arXiv:1505.04597
[6] Simonyan, Karen & Zisserman, Andrew. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv 1409.1556.