Cell Culture Image Classification Using Deep Learning

Talia Gafrick, Koushik Howlader, Dr. Lu Liu, Dr. Williams Calderón-Muñoz

Introduction:

The emergence of deep learning has highlighted the cruciality of transfer learning in numerous fields, particularly in medical imaging. However, the availability of this data is scarce due to quality standards, patient privacy, monetary incentive,etc. Transfer learning has provided a solution to this challenge. This process modifies a pre-trained image neural network architecture by fine-tuning output layers with the smaller target dataset. This poster focuses on the examination of transfer learning with breast and prostate cancer cell culture imaging. The performance of three established deep neural networks- ResNet50, VGG19, and InceptionV3- on a target dataset with various fine-tuning configurations is evaluated.

The Dataset:

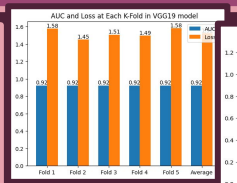
The fine-tuning dataset used is the Wilkinson dataset. It consists of 18 classifications, approximately 90 images per class, and a total of 1632 images. The dataset captures MDA MB 231 (breast cancer) and PC3 (prostate cancer) cells using a phase-contrast microscope with a 10X objective. This is an observation technique of colorless or translucent specimens using a small cone of light. With this method, cells can be captured in their natural state without staining. Meanwhile, the cells were plated at densities of 10k, 20k, and 40k. Post-plating, images were captured after 24, 48, and 72 hours.

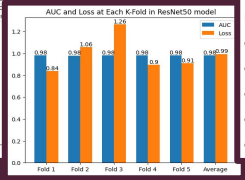
Methodology:

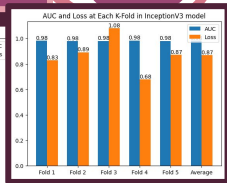
In this study, a balanced distribution of images from each class was achieved through stratified splitting. The dataset was divided into 80% training data and 20% testing data. Transfer learning was applied using pre-trained models based on three deep convolutional neural network architectures- ResNet-50, VGG19, and Inceptionv3- which were originally trained on the ImageNet dataset. After pre-training, the models were fine-tuned on the Wilkinson Dataset. Two models were created for each architecture, one with all layers frozen except the last fully connected layer, and the other with only the last block of layers being trainable. The models were evaluated using 5-Fold cross-validation, ensuring each image was used for both training and testing, leading to more reliable performance estimates and a better representation of generalization ability.

Results:

Across all deep CNN architectures, the models with the last blocks left unfrozen performed significantly better than their counterparts. Results provided from 5-Fold Cross Validation and model comparison on right:







VGG19: 24.38% vs 47.53% accuracy, 2.107 vs 1.522 loss, and 0.7966 vs 0.9234 AUC
ResNet-50: 41.35% vs 68.38% accuracy, 2.635 vs 0.990 loss, and 0.873 vs 0.980 AUC
Inceptionv3: 36.11% vs 71.67% accuracy, 2.085 vs 0.8694 loss, and 0.877 vs 0.9811 AUC

Conclusions:

After creating several transfer learning models using the three deep CNN architectures the models with the last blocks of layers unfrozen performed best. Overall, the Inceptionv3 model with the last block unfrozen yielded the highest accuracy/AUC and lowest loss The ResNet-50 model had comparable results to Inceptionv3. However, the VGG19 model performed significantly worse in comparison to both Inceptionv3 and ResNet-50. There was improved accuracy using deep CNN architectures with trainable layers compared to standard machine learning algorithms overall. The improved performance alongside deep learning model abilities, such as automated feature extraction and rapid data analysis, far outperform humans and create potential for expedited medical developments. The accuracies, losses, and AUCS of the transfer learning models have provided better understanding of MDA MB 231 and PC3 cancer cell behavior, particularly the growth patterns within the first three days of plating, proving deep learning models can provide temporal evolution insights otherwise undetected utilizing standard practices.

Acknowledgements:

The authors acknowledge the support of the NDSU Department of Computer Science sponsored by NSF Directorate for Engineering and EP SCoR Co-Funding through NSF grant EEC-2050175. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References:

[1] K. Howlader and L. Liu, "Transfer Learning Pre-training Dataset and Fine-tuning Effect Analysis on Cancer Histopathology Images," 2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Las Vegas, NV, USA, 2022, pp. 3015-3022, doi: 10.1109/BIBM55620.2022.9995076.
[2] Bulathsinghalage, Chamaka, and Liu, Lu. *Transfer Learning Pre-training Dataset Effect Analysis for Breast Cancer Imaging*. Retrieved from https://par.nsf.gov/biblio/10341883. *EPIC Series in Computing* 83. Web. doi:10.29007/mnx7.
[3]Edlund, C., Jackson, T.R., Khalid, N. et al. LIVECell—A large-scale dataset for label-free live cell segmentation. *Nat Methods* 18, 1038–1045 (2021). https://doi.org/10.1038/s41592-021-01249-6
[4]Y.-T. Su, Y. Lu, J. Liu, M. Chen and A. -A. Liu, "Spatio-Temporal Mitosis Detection in Time-Lapse Phase-Contrast Microscopy Image Sequences: A Benchmark," in *IEEE Transactions on Medical Imaging*, vol. 40, no. 5, pp. 1319-1328, May 2021, doi: 10.1109/TMI.2021.3052854.
[5] He, K., Zhang, X., Ren, S., & Sun, J. (2015). *Deep Residual Learning for Image Recognition*.
[6] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).
[7] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna. 2015. Rethinking the Inception Architecture for Computer Vision. arXiv:1512.00567 [cs.CV]
[8]Jaworek-Korjakowska, Joanna & Kleczek, Pawel & Gorgon, Marek. (2019). Melanoma Thickness Prediction Based on Convolutional Neural Network With VGG-19 Model Transfer Learning. 2748-2758. 10.1109/CVPRW.2019.00333.
[9]H. Cui, D. Wei, K. Ma, S. Gu and Y. Zheng, "A Unified Framework for Generalized Low-Shot Medical Image Segmentation With Scarce Data," in *IEEE Transactions on Medical Imaging*, vol. 40, no. 10, pp. 2656-2671, Oct. 2021, doi: 10.1109/TMI.2020.3045775.
[10] J. Deng, W. Dong, R. Socher, L.-J. Li, Kai Li and Li Fei-Fei, "ImageNet: A large-scale hierarchical image database," *2009 IEEE Conference on Computer Vision and Pattern Recognition*, Miami, FL, USA, 2009, pp. 248-255, doi: 10.1109/CVPR.2009.5206848.
[11]Angulia, D., Ghelardoni, L., Ghio, A., Oneto, L., & Ridella, S. (2012, April). TheKNk K-fold Cross Validation. In *ESANN* (pp. 441-446).