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A Fine-tuned InceptionV3 Convolutional Neural Network (CNN) Architecture Accurately Distinguishes Between Benign and Malignant Breast Histology

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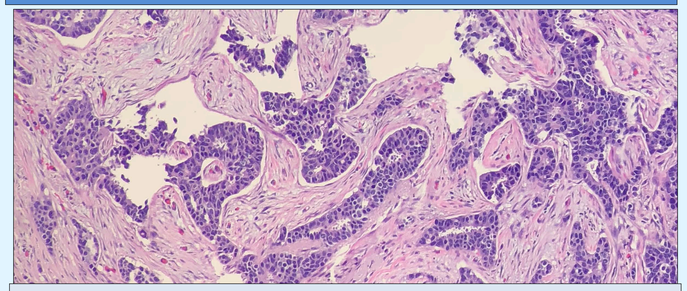
Background

- Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision.
- While application of CNNs in pathology has been increasing, it's utilization is still minimal.
- The majority of popularized studies focus on the identification of malignant cells in a background of normal.
- Multiple studies have been published demonstrating effective classification of common tumors with a focus on whole slide imaging.[1-3]
- No published studies have looked at identification of various classes with the potential to help train resident pathologist, or reduce work load by screening slides through readily available images.
- Here, we demonstrate fine-tuning an InceptionV3 CNN model with relatively few training images accurately and confidently distinguishes between various benign and malignant lesions of the breast.

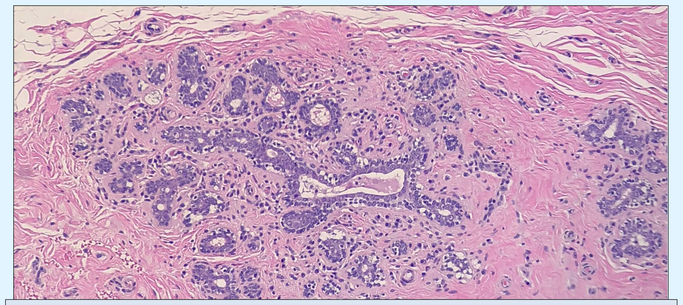
Design

- 4 classes of breast pathology were considered for image analysis:
  - Benign lobules
  - Duct ectasia
  - Ductal carcinoma in situ
  - Invasive ductal carcinoma
- Images were taken by a 12 megapixel smart phone camera at 1.9x zoom at a 10, 20, and 40x microscope lens optics.
- Images were randomly partitioned into training (80%) and validation sets (20%).
- The training set was used to fine-tune a customized fully-connected (FC) layer on top of the InceptionV3 CNN architecture utilizing pre-trained ImageNet convolutional layer weights.
- The customized FC layer contained a single 256-unit hidden layer and 4 final output units with softmax activation to output a probability distribution.
- "Accurate prediction" was defined as the model outputting its maximum probability prediction on the true class.

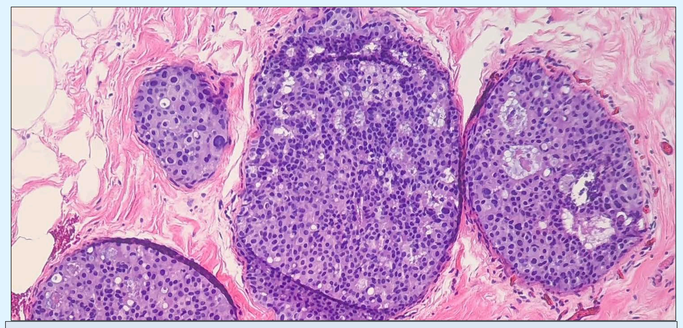
Figure: Predicted probability of 4 images for each class where 1 is 100% probability and 0 is 0% probability of a given class.



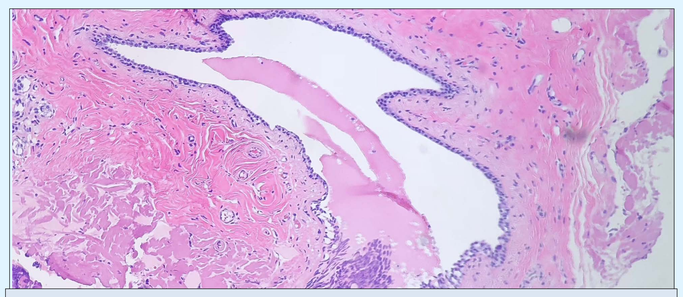
Invasive: 0.998, Duct ectasia: 0.001,
Lobules: 0.001, DCIS: 0.000.



Lobules: 0.882, DCIS: 0.110,
Duct ectasia: 0.008, Invasive: 0.000.



DCIS: 0.4998, Lobules: 0.4997,
Duct ectasia: 0.0003, Invasive: 0.0001.



Duct ectasia: 0.489, DCIS: 0.465,
Invasive: 0.016, Lobules: 0.034.

Results

- A total of 354 images of 4 classes of breast pathology were collected:
  - Benign lobules: 154 images
  - Duct ectasia: 38 images
  - Ductal carcinoma in situ: 84 images
  - Invasive ductal carcinoma: 78 images
- **The CNN showed 100% accuracy.**
  - The mean predicted probability of true class over the entire validation set was 0.959 with a standard deviation of 0.105.
  - 88% of validation images showed a predicted true class probability of ≥ 0.90:
    - 100% of invasive ductal carcinoma.
    - 92.3% of benign lobules.
    - 81.8% of ductal carcinoma in situ.
    - 71.4% of ducts ectasia.
  - Two validation images showed at true class probability of less than 0.5 (0.486 and 0.499).
    - Both images with >0.5 were DCIS versus benign lobules or duct ectasia.

Conclusion

- Fine-tuning the InceptionV3 architecture provides a remarkably accurate and confident CNN model to distinguish between malignant and benign classes in breast pathology.
- Importantly, adequately InceptionV3 can be trained and validated with extremely accessible cameras/optics such as a smart phone camera.
- Large models could provide framework for real-time resident learning and reduced pathologist workload.

References

1. Sornapudi S, Stanley RJ, Stoecker WV, et al. Deep learning nuclei detection in digitized histology images by superpixels. J Pathol Inform. 2018 Mar 5;9:5.
2. Couture HD, Williams LA, Geradts J, et al. Image analysis with deep learning to predict breast cancer grade, ER status, histologic subtype, and intrinsic subtype. Npj Breast Cancer (2018)4:30.
3. Dayong W, Aditya K, Rishab G, et al. Deep learning for identifying metastatic breast cancer. Camelyon Grand Challenge 2016.