Diagnostic Assessment of Breast Cancer in Non-Contrast MRI Images Through an Artificial Intelligence Machine Learning Algorithm

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Synopsis

Contrast-Enhanced Breast MRI is a common method for diagnosis of Breast Cancer. An Artificial Intelligence Machine Learning Algorithm was developed to analyze Non-Contrast Breast MRI scans and predict diagnoses. The algorithm was trained using MRI data that had pathological specimens to validate diagnoses, obtained from The Cancer Imaging Archive. The AI was found to be 95% accurate in classifying tissue as cancerous or benign. This algorithm could be used to assist diagnoses in clinical practice. Future work will assess the generalizability of the algorithm on data from other scan sites, and the potential for classifying specific subtypes of Breast Cancer.

Introduction

Breast MRI offers advantages over mammography by not exposing patients to ionizing radiation, but relies on administration of intravenous Contrast Agents¹. Artificial intelligence (AI) machine learning algorithms for Computer Assisted Diagnosis are software packages that intake labelled images of different classes (i.e. cancerous images and benign images) and create statistical functions that explain the variance between classes². AI uses learning theories and training algorithms which mimic techniques used in clinical training. AI offers a way to aid clinicians in diagnostic accuracy by applying quantitative algorithms on individual pixel values of images²,³,⁴,⁵. This study sought to develop an AI approach to accurately and efficiently differentiate cancerous from benign tissue.

Methods

Non-contrast T2-weighted Turbo spin echo MRI images of 21 Patients with confirmed Breast Cancer (n = 21) and Patients without Breast Cancer (n = 9) were obtained from the BREAST-DIAGNOSIS⁶ collection of The Cancer Imaging Archive⁷, totaling 2,766 independent slices. All cancer diagnoses had corresponding pathological specimens for validation. An AI system using a Convolutional Neural Network (CNN) was built through Python scripting language to accurately identify specific imaging characteristics. The framework used was Google's™ Tensorflow© 1.3.0, built to utilize the Graphical Processing Unit (GPU). A gradient descent algorithm was used to train the algorithm and minimize the loss function. The pipeline accepts both DICOM and NIfTI file types as inputs, although the BREAST-DIAGNOSIS data is in DICOM format. DICOM volumes were converted to single-slice JPEG images and labelled as cancerous or benign. Validation accuracy was calculated as the percentage of calculated classifications that matched pathological diagnosis, using a 10% holdout threshold. Images were randomly shuffled and parsed into either training (90%) or testing (10%) data groups. Images that were used to train the algorithm were not used to test the algorithm. Efficiency was determined in seconds per slice⁸. Our algorithm was trained and assessed using the unprocessed, native images that were acquired.

Results

Using our neural network AI, tissue was classified as cancerous or benign with a validation accuracy of 95%. The algorithm was trained for 10,000 steps at a rate of 100ms per step, meaning that the algorithm was trained, tested, then re-trained with tuned parameters 10,000 times to increase accuracy (Figure 1). The AI classifies images at a rate of 2.28 seconds/slice, and automatically iterates through each slice of a volume.

Discussion

Other CNN's using TensorFlow have shown diagnostic accuracies up to 60.9% in classifying mammograms⁹. Our study has shown a diagnostic accuracy of up to 95% in pathologically-validated subset of Patients using Breast MRI. One of the challenges in any quantitative analysis of medical images is the variability in patient anatomy and image acquisition parameters⁵,⁹,¹⁰. The data used in this project were all collected using the same 1.5T Philips© Achieva™ MRI scanner and TSE SENSE¹¹ pulse sequence. This simplified our analysis, since we did not need to correct for differences in image weighting. However, this also means the generalizability of the algorithm to other scan sites is untested. Our classifier was constructed to differentiate slices as cancerous or benign, but could potentially be trained to specifically identify types of cancer (e.g., invasive ductal carcinoma vs. invasive lobular carcinoma). This could expand the algorithm's clinical usefulness, if successful. We used a high-powered workstation to train and assess the neural network; the Windows™ PC contained 64GB of RAM, a CPU overclocked to 4.1GHz, and an 8GB GeForce© GTX 1080™ GPU. A workstation equipped with lower-grade hardware would not process as quickly, but theoretically would produce the same results. It is common practice to pre-process images before assessment with a machine learning algorithm, using techniques such as segmentation, smoothing or normalization. Further work can assess the ability to specifically classify tumor types, the effect of pre-processing on classification accuracy, and the algorithm's generalizability to other scan sites and pulse sequences.

Conclusion

CNN offers a novel way to accurately identify Patients with Breast Tumors using non-contrast MRI images. This has important clinical applications for non-invasive Breast Cancer detection, diagnosis and assessment, as well as differentiation of tumor subtypes, facilitating optimized treatment decisions and optimizing treatment planning for the individual patient. Al algorithms can be trained to detect individual tumor characteristics, allowing clinicians to identify aspects of the tumor and its individual behavior prior to treatment and for disease monitoring⁶,¹⁰,¹¹. Further work can assess the ability to specifically classify tumor types, the effect of pre-processing on classification accuracy, and the algorithm's generalizability to other scan sites and pulse sequences.

Acknowledgements

We would like to acknowledge The Cancer Imaging Archive, and specifically the team from the BREAST-DIAGNOSIS study, for curating this dataset and making it freely available to the public. Without their efforts, we would not have been able to complete this research.

References


**Figures**

Algorithm Learning Rate depicting accuracy improvements over training steps.