Enhancing Breast Cancer Diagnostics: Swin Transformer for Histopathology Image Classification

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Introduction

Breast cancer remains a leading cause of cancer-related mortality worldwide, with early and accurate diagnosis critical for improving patient outcomes. Histopathological image analysis is a cornerstone of breast cancer diagnosis but is labor-intensive and subjective, relying heavily on pathologists' expertise. Advances in artificial intelligence (AI), particularly deep learning, offer potential solutions to automate and enhance diagnostic workflows. The Swin Transformer, a state-of-the-art vision model, leverages hierarchical feature extraction and self-attention mechanisms to achieve superior performance in image classification tasks. This study aimed to evaluate the effectiveness of a pretrained Swin Transformer model in classifying benign and malignant breast cancer histopathology images using the BreakHis dataset.

Hypothesis

We hypothesized that the Swin Transformer, fine-tuned on the BreakHis dataset, would achieve high classification accuracy, sensitivity, and specificity in distinguishing between benign and malignant breast tumor images across multiple magnifications.

Methods

Data Preparation and Preprocessing:
The BreaKHis dataset, a publicly available collection of breast histopathology images captured at 40x, 100x, 200x, and 400x magnifications, was reorganized into two simplified directories: benign and malignant. A CSV file was used to track image metadata, including class labels and magnification levels. Images were renamed to align with patient IDs. Data were split into training (80%), validation (10%), and test (10%) sets.
Data Augmentation and Model Training:
To simulate real-world diagnostic variability, data augmentation was applied, including resizing, cropping, flipping, rotation, and color jittering. The Swin Transformer model, pre-trained on the ImageNet dataset, was retrained to classify histopathology images. The model was trained using the Adam optimizer with a learning rate of 1e-4.
Model Validation:
The model was validated against test datasets, and key performance metrics such as accuracy, sensitivity, specificity, and AUC were used to assess its potential integration into clinical workflows.

Results

The Swin Transformer model achieved an accuracy of 97.72%, sensitivity of 99.27%, and specificity of 92.15%, with an AUC of 0.9571. These results suggest that the model could provide significant clinical value by aiding pathologists in making more accurate and timely breast cancer diagnoses.

Conclusion

We demonstrate the potential of advanced deep learning models, such as the Swin Transformer, in augmenting breast cancer diagnostics. The integration of such technologies in healthcare settings could improve diagnostic accuracy and speed, reduce the dependency on specialized pathologists, and allow pathologists to make quicker treatment decisions, directly impacting patient outcomes. Future studies will focus on using the Swin Transformer to classify MRI scans of breast cancer into benign and malignant categories.

Figure(s)

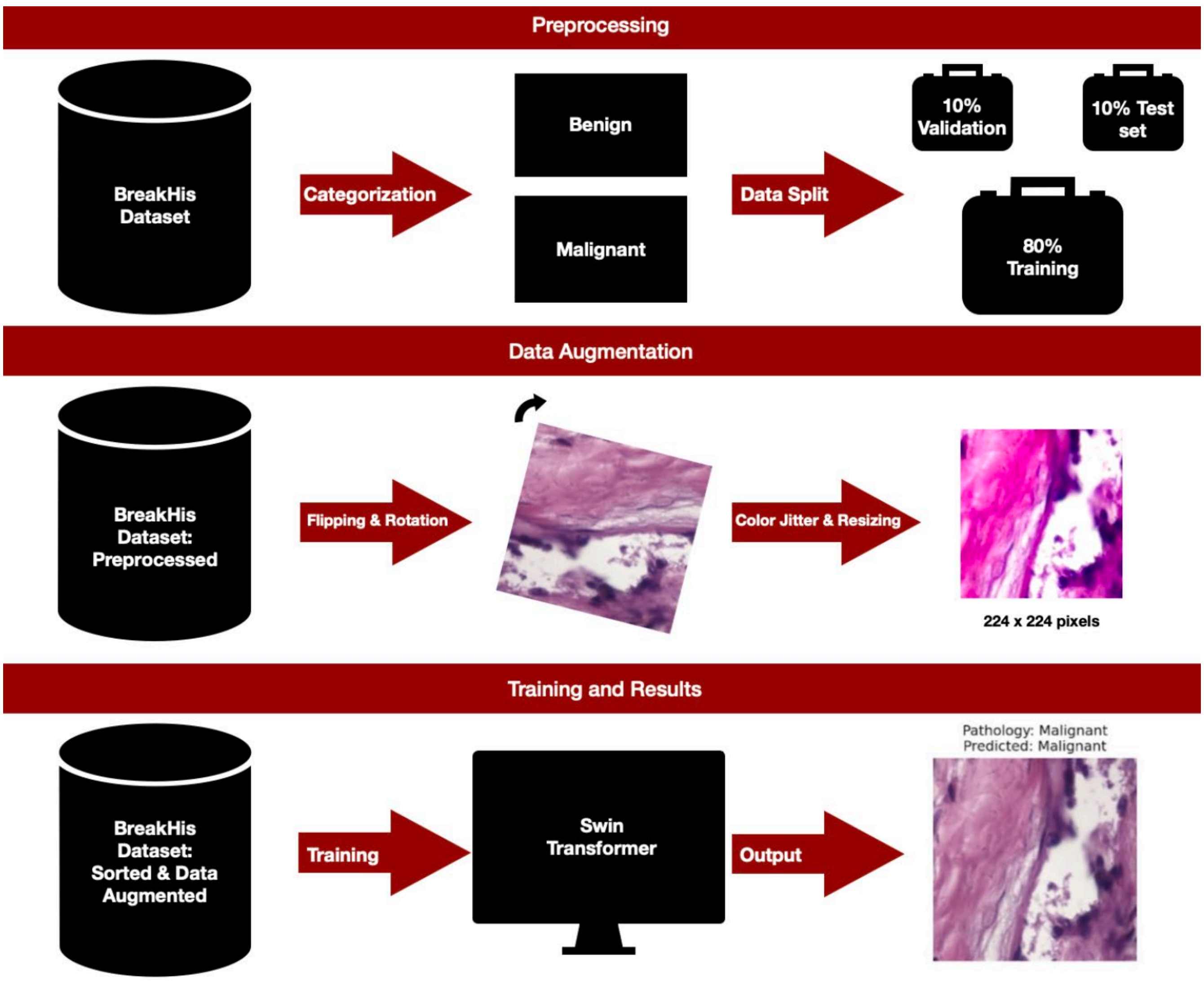

Figure 1. Graphic of Preprocessing, Data Augmentation, and Training Process

AUC Score	0.9571
Sensitivity	0.9927
Specificity	0.9215
Accuracy	0.9772

Table 1. AUC Score, Sensitivity, Specificity, and Accuracy of Pre-Trained Swin Transformer for Binary Classification of BreakHis Dataset

Keywords

Applications; Artificial Intelligence/Machine Learning; Imaging Research