Quantum Enhanced Histopathologic Cancer Detection

by

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A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Science

Approved October 2024 by the
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December 2024

ABSTRACT

This study explores the integration of quantum machine learning techniques to improve the detection of metastatic cancer in histopathological images, using the PatchCamelyon (PCam) dataset. A hybrid approach is implemented, incorporating quantum image preprocessing methods such as quantum filtering, quantum edge detection, and quantum convolution into established convolutional neural networks (CNNs) including VGG, ResNet, and UNet architectures. Quantum preprocessing techniques demonstrate improved sensitivity in detecting cancerous regions, although there are challenges in balancing sensitivity and specificity. Classical models achieve an accuracy of up to 94.6%, while the hybrid quantum-classical models show potential in enhancing feature extraction and diagnostic accuracy.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my advisor, Professor Andreas Spanias, for his invaluable guidance throughout the course of this research. I am equally grateful to my mentor, Glen Uehara, whose expertise and continual support have been instrumental in the completion of this work. This work would not have been possible without the resources provided by the SenSIP Center.

I would also like to extend my deepest gratitude to my family, whose unwavering love and support have been the foundation of my success.

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INTRODUCTION

1.1 Research Overview

Cancer, a widespread global health issue, has become the primary cause of death worldwide, including various types such as lung, liver, colorectal, stomach, and most notably, breast cancer (Luz, Lima, Silva, Magalhães, & Araujo, 2022). The seriousness of this situation is highlighted by a significant increase in cancer cases, with projections suggesting 2.7 million new cases by 2030 (Łukasiewicz, Błaszczak, Jakubowski, Kłosowski, & Małek, 2021). Breast cancer, being one of the most prevalent and lethal types, emphasizes the importance of accurate and timely diagnoses (Xie, Liu, Luttrell, & Zhang, 2019). Detecting cancer early and accurately is crucial for effective treatment and improved patient outcomes, making it a critical focus in healthcare.

1.2 Motivation

Histopathology, a crucial step in studying cancer development, involves the microscopic examination and detailed evaluation of biopsy samples from affected organs (He, Wu, & Ma, 2022). While traditional histopathological analysis is essential, it presents challenges due to its time-consuming nature and reliance on the expertise of pathologists (He, Wu, & Ma, 2022). The manual examination of histopathological images, a key aspect of cancer diagnosis, has limitations in terms of efficiency and consistency (Xie, Liu, Luttrell, & Zhang, 2019). To tackle these issues, there is a growing interest in incorporating technology, particularly computer-assisted image analysis, to enhance diagnostic capabilities.

1.3 Problem Statement

Traditional biopsy techniques, including fine-needle aspiration and surgical biopsy, remain crucial for diagnosing breast cancer, with histopathological analysis as the gold standard (Ahmad, Ahmed, Ouameur, & Jeon, 2022). However, manual analysis of histopathological images encounters challenges including subjectivity, inconsistency, and time consumption (Xie, Liu, Luttrell, & Zhang, 2019). These limitations hinder the efficiency and reliability of cancer diagnoses, underscoring the need for automated, accurate, and efficient diagnostic tools. In response, computer-aided analysis, especially utilizing deep learning techniques, has gained prominence (Xie, Liu, Luttrell, & Zhang, 2019).

1.4 Related Work

Researchers have explored various machine learning approaches to automate histopathologic image analysis. Studies have shown the effectiveness of deep learning models, such as CNNs, in automating cancer detection tasks. Notably, studies by Ahmad et al. (2022) and Jaiswal et al. (2019) demonstrated high accuracy in classifying histopathologic scans of lymph node sections using CNN architectures. Ensemble deep learning approaches, as demonstrated by Kassani et al. (2019) and Luz et al. (2022), have also yielded promising results on the PCam dataset.

In the realm of quantum computing, Majumdar et al. (2023) introduced quantum transfer learning for histopathological cancer detection, achieving comparable accuracy to classical models by combining classical architectures with variational quantum circuits (VQC). Azevedo, Silva, & Dutra (2022) demonstrated the efficacy of quantum machine learning (QML) in breast cancer detection, achieving significant improvements in accuracy and AUC values with classical-quantum hybrid models.

1.5 Research Approach

I propose developing a hybrid model that integrates classical machine learning with quantum computing techniques to enhance the accuracy and efficiency of cancer detection in histopathological images. By leveraging the strengths of both classical CNN architectures like ResNet-50 and advanced quantum algorithms, my approach aims to provide a 'quantum advantage' through improved feature extraction (Krishna, 2024) and classification accuracy.

1.6 Dataset, Challenges, and Preprocessing

In the field of machine learning, MNIST (handwritten digit recognition; *Torchvision*, n.d.) and CIFAR (color image classification; *PyTorch*, n.d.) have become standard benchmarks for evaluating the effectiveness of image recognition algorithms. These benchmarks also allow researchers to experiment with and refine their models before deploying them in more sophisticated applications. More advanced applications, for example, medical imaging, demand more complex datasets that capture the intricate details of that domain. This shift highlights the need for datasets like the PatchCamelyon (PCam) benchmark, which focuses on the emerging field of medical image analysis.

The PCam dataset comprises 327,680 color images, each measuring 96 x 96 pixels (Basveeling, n.d.). The images are taken from histopathologic scans of lymph node sections. Every image in the PCam dataset is marked with a binary label that signifies the presence or absence of metastatic tissue. PCam simplifies the complex task of identifying metastasis tissue to a straightforward binary image classification problem, allowing for increased efficiency in training, practicality, and operational performance (Basveeling, n.d.). I am using the Kaggle version of the PCam dataset that has been modified to remove duplicate samples that were present in the original dataset due to its probabilistic sampling (Kaggle, n.d.). Refer to Fig.1.

Initially, I used IBM Quantum Composer and IBM Quantum Lab (IBM Quantum, n.d.) to design and simulate the circuits. After a few months, I transitioned to using the Qiskit and Keras frameworks for this purpose.

During this study, I encountered several challenges, primarily related to the extended run times and the complexity of the data. Quantum processing of the highdimensional images (96x96x3) was particularly time-consuming, with each image taking anywhere from 2 to 10 minutes depending on the method. Training the models, both classical and hybrid, resulted in long run times, taking days, sometimes weeks, to complete due to hardware limitations. To address this, I worked with a smaller portion of the dataset for hybrid techniques, while using the full dataset for classical models, which were better suited for handling the larger data volume.

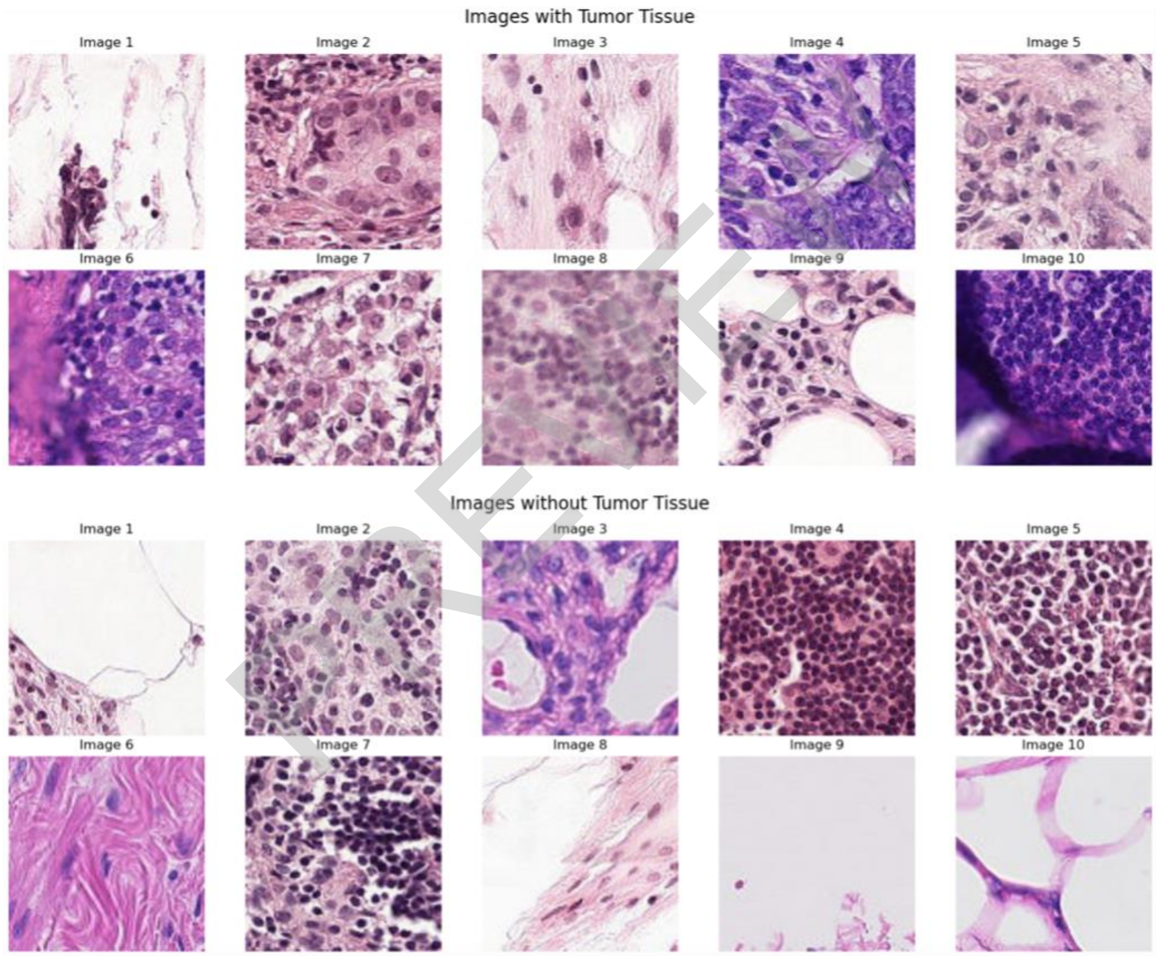

Figure 1. Samples of Cancerous (top) and Non-Cancerous (bottom) Sections from the PCam Dataset

CHAPTER 2

LITERATURE REVIEW

2.1 Machine Learning and Cancer Detection

Deep learning models, especially convolutional neural networks (CNNs), have been proven effective in medical image analysis. Their ability to identify patterns and detect subtle features in large datasets has made them highly effective for tasks like cancer detection.

In their study, Yang et al. (2022) conducted a comprehensive evaluation of various methods for medical image classification. They compared the performance of different models, including ResNet-18 and ResNet-50 architectures with varying input resolutions (28 and 224), as well as auto-sklearn, AutoKeras, and Google AutoML Vision. For the PathMNIST dataset, which involves multi-class classification of colon pathology images, the results revealed that the deeper ResNet-50 model, despite having a lower input resolution of 28, achieved superior performance compared to the shallower ResNet-18 architecture (Yang et al., 2022). The ResNet-50 model attained an AUC of 0.979 and an ACC of 0.864 (Yang et al., 2022). This suggests that the increased model depth and complexity contribute to better feature extraction and classification accuracy, particularly in the context of histopathologic image analysis.

Furthermore, the comparison with other methods highlights the effectiveness of deeper convolutional neural network (CNN) architectures, such as ResNet-50, in accurately classifying histopathologic images for cancer detection. While Google AutoML Vision also demonstrated competitive performance, achieving an AUC of 0.982 and an ACC of 0.811, ResNet-50 outperformed it in terms of accuracy metrics (Yang et al., 2022).

The reviewed literature presents results from various studies utilizing classical machine learning models on the PCam dataset, demonstrating high accuracies achieved by models such as VGG-16, ResNet-50, and others.

Ahmad et al. (2022) presented a comprehensive study on the classification and detection of cancer in histopathologic scans of lymph node sections using CNNs. Their CNN architecture, comprising of five convolution layers, batch normalization, ReLU activation, max-pooling layers, and a fully connected layer, achieved an accuracy of 98% on the dataset. Additionally, they evaluated pre-built models like VGG-16 (94%), ResNet-50 (96%), Inception (96%), and CapsNet (93%) (Ahmad et al., 2022).

Jaiswal et al. (2019) implemented a semi-supervised learning strategy with various pre-trained models. Notable results were achieved across multiple models, including VGG-16 (97.45%), InceptionResNetV2 (97.66%), Xception (97.52%), InceptionV3 (97.74%), SE-ResNet101 (97.83%), Densenet201 (97.94%), and GDenseNet (96.30%) (Jaiswal et al., 2019).