Literature Review

Introduction

A well-structured literature review provides a theoretical foundation for a research project, helps identify knowledge gaps, and justifies methodological choices. This review focuses on artificial intelligence-driven Convolutional Neural Networks (CNNs) for histopathology image classification, specifically for detecting metastatic breast cancer. The selection of MM-SEN, DenseNet-121, and EfficientNet-B0 for this project is informed by existing literature, which highlights their strengths in medical image classification.

1. Ge *et al.* (2024)

Tumour detection in breast cancer pathology patches using a Multi-scale Multi-head Self-attention Ensemble Network on Whole Slide Images
Source: *Machine Learning with Applications*
DOI: 10.1016/j.mlwa.2024.100592

Ge *et al.* (2024) introduce Multi-scale Multi-head Self-attention Ensemble Network (MM-SEN), an advanced CNN architecture designed to improve tumour detection in whole-slide histopathology images (WSIs). Their research highlights several key advantages of MM-SEN:

- Multi-scale feature extraction enhances the model's ability to learn spatially diverse histological features.
- Multi-head self-attention improves contextual understanding, making the model more effective in differentiating cancerous vs. non-cancerous tissue.
- MM-SEN outperforms traditional CNNs (ResNet34, VGG19, etc.) in tumour classification tasks.

Given the complexity of metastatic breast cancer classification, MM-SEN's ability to capture hierarchical spatial features and enhanced attention mechanisms make it a strong candidate for this research. It is expected to improve diagnostic accuracy by reducing inter-observer variability, a major limitation in traditional pathology.

2. Zhong et al. (2020)

Cancer image classification based on DenseNet model
Source: *Journal of Physics: Conference Series*
DOI: 10.1088/1742-6596/1651/1/012143

Zhong et al. (2020) evaluate DenseNet-121, a deep learning model that utilises dense connections between layers to improve feature propagation and reduce redundancy. The study highlights:

- Dense connectivity mitigates the vanishing gradient problem, improving performance in deep networks.
- Efficient parameter usage leads to better generalisation with fewer parameters than ResNet and VGG.
- Superior accuracy compared to other CNNs, particularly in cancer image classification tasks.

DenseNet-121 is chosen because of its high accuracy in medical image classification and efficient feature extraction. The model's ability to retain feature information across layers is crucial for distinguishing subtle histopathological patterns, making it highly suitable for PCam dataset classification.

3. EfficientNet-B0

Tan, M., & Le, Q. V. (2019). *EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks.* In *Proceedings of the 36th International Conference on Machine Learning (ICML)*, pp. 6105-6114. Available at: https://arxiv.org/abs/1905.11946

This paper presents EfficientNet, a family of CNN architectures that optimize scaling across depth, width, and resolution, with EfficientNet-B0 being the baseline model. It achieves high classification accuracy with significantly fewer parameters compared to traditional CNNs like ResNet and DenseNet.

- Scaling efficiency, using a compound scaling technique that balances width, depth, and resolution for optimal performance.
- Higher accuracy with fewer parameters, making it computationally efficient compared to larger models.
- Strong performance in medical imaging, demonstrated in multiple AI-driven pathology studies.

EfficientNet-B0 is selected for comparison due to its computational efficiency and strong classification accuracy. While MM-SEN and DenseNet-121 focus on feature enhancement and connectivity, EfficientNet-B0 provides a lightweight yet powerful alternative, making it suitable for real-time applications and resource-constrained environments.

4. Veeling *et al.* (2018)

Rotation Equivariant CNNs for Digital Pathology
Source: *International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*
DOI: arXiv:1806.03962

Veeling *et al.* (2018) introduce the PatchCamelyon (PCam) dataset, a widely used benchmark dataset for binary classification of histopathology images. The dataset is derived from CAMELYON16 and consists of:

- 327,680 labelled image patches (96×96 pixels), allowing for efficient deep learning training.
- Binary classification format (tumour vs. non-tumour), making it ideal for evaluating CNN-based models.
- Pre-processed and well-annotated data, ensuring high-quality training and evaluation.

Relevance to my Research

Using PCam ensures consistency with prior studies and enables comparison of model performance on a standardised dataset. Its large size and rich histological variations make it an excellent choice for training deep learning models.

Conclusion

This literature review not only provides an overview of key CNN architectures for histopathology image classification but also explicitly links the choice of MM-SEN, DenseNet-121, and EfficientNet-B0 to previous research:

- MM-SEN is chosen for its multi-scale feature learning and self-attention mechanisms, which enhance tumour detection accuracy.
- DenseNet-121 is selected due to its efficient feature reuse and superior performance in cancer classification.

- EfficientNet-B0 is included as a lightweight yet powerful alternative, offering high accuracy with lower computational cost.
- PCam is the dataset of choice because of its wide acceptance in AI-driven pathology research, enabling effective benchmarking of CNN models.

This justifies the model selection based on a combination of accuracy, efficiency, and suitability for medical imaging tasks. By leveraging insights from previous research, this project aims to develop an optimised CNN-based AI model for improving breast cancer detection in histopathology images.