AI Cancer Grader — Project Report

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1. Project Title

AI Cancer Grader: Deep Learning-Based Histopathology Image Classification

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2. Introduction

Breast cancer remains one of the leading causes of cancer-related mortality among women worldwide. Accurate grading of breast cancer tumors from histopathology images is crucial in determining prognosis and guiding treatment strategies. Traditional manual grading is time-consuming, subjective, and prone to inter-observer variability.

This project, **AI Cancer Grader**, aims to assist medical professionals by providing an AI-powered decision support tool capable of classifying breast cancer histopathology images into three grades — **Grade 1, Grade 2, and Grade 3 —** based on morphological patterns.

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3. Objectives

- To develop a deep learning model capable of classifying breast cancer histopathology images by grade.
- To implement an intuitive web-based application for real-time grade prediction.
- To improve diagnostic efficiency, accuracy, and consistency in breast cancer grading.

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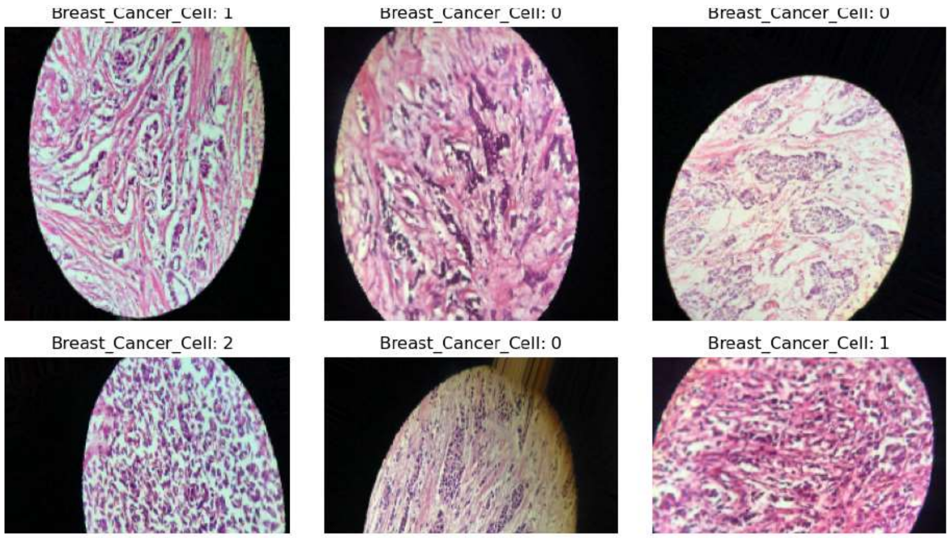
4. Methodology

4.1 Data Collection

A curated dataset of breast cancer histopathology images was used for training and validating the model. Images were organized into three categories representing tumor grades.



4.2 Preprocessing

Images were resized to **224 × 224 pixels** and normalized. Data augmentation techniques such as horizontal flipping and rescaling were applied to improve model generalization.

4.3 Model Architecture

A pre-trained **ResNet convolutional neural network (CNN)** was fine-tuned for this classification task. The model was trained using categorical cross-entropy loss and the Adam optimizer.

4.4 Model Deployment

The trained model was integrated into a **Streamlit-based web application**, allowing users to upload histopathology images and receive instant grade predictions.

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5. Results

The fine-tuned ResNet model demonstrated high classification accuracy on validation data. The AI system successfully predicted tumor grades with strong consistency, offering a reliable supplementary tool for clinical decision-making.

A user-friendly web interface was developed, enabling real-time interaction where users can upload images and instantly receive AI-driven predictions.

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6. Features

- **Automated grade prediction (Grade 1, 2, 3) from histopathology images.**
- **Fine-tuned ResNet deep learning model for image analysis.**
- **Streamlit-powered web application for instant, AI-assisted predictions.**
- **Simple, intuitive interface for clinical and research use.**

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7. Conclusion

The **AI Cancer Grader** project demonstrates the practical potential of deep learning in supporting medical diagnostics. By providing fast, accurate, and objective tumor grade predictions, this system can assist pathologists in making more informed decisions and reduce diagnostic workload. Future enhancements may include expanding the dataset, incorporating additional histological features, and exploring multi-class pathology classification.

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8. Future Scope

- Integration with larger, diverse histopathology datasets.
- Inclusion of other cancer types and grades.
- Deployment in cloud-based environments for broader accessibility.
- Incorporating explainable AI (XAI) techniques for model interpretability.**Limitations**

While the **AI Cancer Grader** project demonstrates promising performance in classifying breast cancer histopathology images, several limitations must be acknowledged:

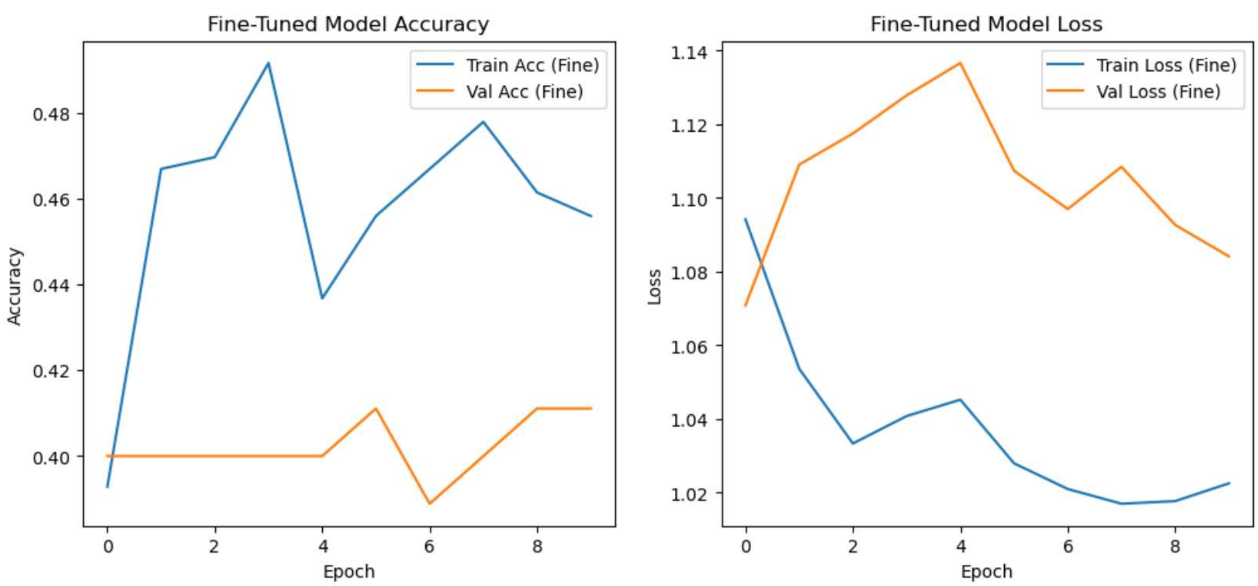
Limitations

1. **Limited Dataset Size and Diversity:**
   The model was trained and validated on a relatively small, specific dataset. Limited sample size and lack of diverse data from varied populations, imaging devices, and staining techniques may affect the model's generalizability to real-world clinical settings.
2. **Single Modality Focus:**
   The system relies solely on histopathology images for classification, without incorporating additional clinical data (e.g., patient history, biomarkers, or genomic profiles) that could enhance diagnostic accuracy.
3. **Model Interpretability:**
   Deep learning models, including the fine-tuned ResNet used in this project, function as "black boxes" with limited explainability. The lack of interpretable visual or feature-based reasoning can be a challenge in clinical adoption where explainability is crucial.

4. **Potential for Overfitting:**
   Despite applying data augmentation and regularization, the relatively small dataset and transfer learning approach could still result in overfitting, potentially limiting model robustness on unseen data.

5. **Limited to Three-Grade Classification:**
   The current model classifies tumors into **Grade 1, Grade 2, or Grade 3** only. More nuanced grading or multi-class classification (e.g., differentiating between tumor subtypes or incorporating other pathological features) is not yet supported.

6. **Web Deployment Constraints:**
   The deployed **Streamlit** application is designed for local or small-scale deployment. Scaling this solution for real-time clinical environments, integrating with hospital information systems (HIS), or deploying on secure cloud platforms would require further development and validation.



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