IDC Breast Cancer Histopathology Classification using Fusion CNN and Explainable AI

Project Overview

Breast cancer is one of the leading causes of cancer-related deaths among women worldwide. Detecting invasive ductal carcinoma (IDC) early can dramatically improve patient outcomes. This project focuses on using deep learning to automatically classify IDC presence from histopathology image patches.

The solution leverages a fusion of multiple Convolutional Neural Networks (CNNs) to enhance feature learning, combined with explainable AI (XAI) methods to provide transparency into the model's decisions. This project is designed to be robust, expandable, and understandable even for those beginning their journey into AI in healthcare.

Goals

- Build a strong, generalizable deep learning model for IDC detection.
- Integrate explainability tools to interpret model predictions.
- Create a framework that is extendable for real-world medical applications.

Techniques Used

1. Fusion CNN Model

- **Backbones Used**: EfficientNetB0, ResNet50, DenseNet121.
- Instead of relying on a single model, multiple powerful CNNs are combined to capture richer features and increase model robustness.
- Fusion was performed at the feature extraction level, aggregating different perspectives from each backbone.

2. Balanced Sampling

- Selected **60,000 patches** from the original dataset (30,000 IDC-positive and 30,000 IDC-negative).
- Balancing ensures that the model does not become biased toward one class, which is critical for medical applications where false negatives can be dangerous.

3. Data Augmentation

- Real-time transformations like horizontal flips, slight rotations, and zooms were used.
- This simulates clinical variability (different microscope settings, sample preparations) and teaches the model to generalize better.

4. Class Imbalance Handling

- **Class weights** were calculated and applied during training.
- This gives more importance to minority samples during optimization and prevents the model from ignoring the less frequent class.

5. Stratified Splitting

- The dataset was split into train, validation, and test sets while maintaining equal proportions of each class.
- Stratification preserves class balance across splits, providing a fair evaluation.

6. Explainable AI (XAI)

- **Saliency Maps** highlight which parts of an image influenced the model's decision.
- **Grad-CAM** (Gradient-weighted Class Activation Mapping) provides localized heatmaps, visually explaining what regions the model is focusing on when making a classification.
- These techniques are crucial for trust and transparency, especially in medical AI.

Dataset Information

- **Name**: IDC Breast Cancer Histopathology Dataset
- **Source**: Public dataset available for research and educational use.
- **Image Size**: 50x50 pixel patches.
- **Content**: Labeled images indicating presence (1) or absence (0) of IDC.

Tools and Frameworks

- **TensorFlow** and **Keras** for deep learning model building and training.

- **Matplotlib** and **OpenCV** for image handling and visualization.
- **Scikit-learn** for preprocessing utilities like stratified sampling.
- **Pandas** and **NumPy** for data manipulation.

Project Highlights

- Successfully curated and trained on a **balanced 60,000 image dataset**.
- Applied **multi-backbone fusion** to extract stronger feature representations.
- Used **real-world inspired data augmentations** to simulate practical variances.
- Embedded **explainability methods** to ensure model decisions are interpretable.
- Maintained scientific rigor through **class balancing** and **stratified splits**.

Future Directions

- Scale up training using the complete IDC dataset for even better generalization.
- Explore ensemble techniques combining multiple fusion models.
- Integrate more advanced explainability techniques like SHAP for deeper insights.
- Move towards **patient-level** prediction by combining patch outputs into full-slide assessments.

Conclusion

This project showcases the successful integration of powerful deep learning models with explainable AI techniques in the field of medical imaging. It balances performance with transparency, laying a strong foundation for future work in building trustworthy AI solutions for healthcare.

Whether you are new to AI or an experienced practitioner, this project demonstrates key practices like balanced dataset preparation, model interpretability, and structured pipeline design — critical components for real-world medical AI deployments.

Thank You

This project is a small step towards democratizing AI in healthcare. Special thanks to the creators of the IDC dataset and the open-source community.