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MULTI-MODAL DEEP LEARNING FRAMEWORK FOR BREAST CANCER DETECTION USING MAMMOGRAM AND HISTOPATHOLOGICAL IMAGES

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ABSTRACT

Breast cancer remains one of the leading causes of mortality among women worldwide, necessitating the development of efficient and accurate diagnostic tools. This project presents an advanced deep learning-based diagnostic framework that integrates dual imaging modalities: mammogram and histopathological images, for enhanced breast cancer detection. The system is developed using Python as the backend language, Flask as the web framework, and HTML, CSS, and JavaScript for the frontend interface. For the mammogram analysis, two separate convolutional neural network architectures, Xception and MobileNet, were employed. The mammogram dataset comprises 3,044 training images classified into four BI-RADS categories: BI-RADS 1 (1865 images), BI-RADS 3 (387), BI-RADS 4 (408), and BI-RADS 5 (384). The Xception model achieved a training accuracy of 96% and a test accuracy of 90%, while the MobileNet model demonstrated superior generalization with a training accuracy of 96% and a test accuracy of 94%. In parallel, the histopathological image classification module utilizes the DenseNet201 architecture to distinguish between benign and malignant tissue samples using the BreakHis 400X dataset. This dataset includes 1,693 high-resolution biopsy images, with 371 benign and 777 malignant images used for training and 176 benign and 369 malignant images for testing. The DenseNet201 model achieved a training accuracy of 98% and a validation accuracy of 88%. The system provides a comprehensive performance analysis based on Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. MobileNet recorded an accuracy of 94.3%, precision of 81.7%, recall of 94.3%, and F1-score of 94.3%, outperforming the Xception model, which achieved an accuracy of 90.7%, precision of 72.3%, recall of 90.7%, and F1-score of 90.7%. For the histopathological analysis, DenseNet201 achieved an accuracy of 88.1%, precision of 91.3%, recall of 88.1%, and F1-score of 88.1%. Additionally, class distribution statistics are visualized to illustrate the dataset balance and support interpretability. By combining radiological and microscopic imaging modalities, this project offers a robust and intelligent diagnostic solution for breast cancer, enhancing early detection and assisting clinical decision-making with improved accuracy and reliability.

1.INTRODUCTION

Breast cancer is one of the most prevalent and life-threatening malignancies affecting women worldwide. Early detection and accurate diagnosis are critical for improving patient survival rates and enabling timely treatment interventions. Traditionally, breast cancer diagnosis relies on radiological imaging techniques such as mammography and confirmatory pathological examination through histological analysis. However, these processes are often time-consuming, require highly skilled medical personnel, and are subject to human interpretation variability, which may lead to misdiagnosis or delayed treatment. Recent advances in artificial intelligence (AI) and deep learning have revolutionized the field of medical imaging by enabling automated and highly accurate diagnostic systems. Deep convolutional neural networks (CNNs), in particular, have demonstrated exceptional performance in image classification tasks across various domains, including healthcare. In breast cancer detection, AI systems trained on large-scale image datasets can assist clinicians by providing fast, objective, and reproducible diagnoses. This project introduces a novel dual-modality deep learning framework for breast cancer detection using both mammogram images and histopathological images. By combining macroscopic radiological imaging with microscopic tissue-level information, the system aims to simulate the real-world diagnostic workflow followed by radiologists and pathologists. The mammogram analysis module is developed using two CNN architectures—Xception and MobileNet—trained to classify images into BI-RADS categories. In parallel, a second module based on the DenseNet201 architecture is used to classify high-resolution histopathological images as benign or malignant. The project is implemented using Python for backend processing, Flask as the web framework, and HTML, CSS, and JavaScript for frontend development, resulting in a user-friendly, web-based diagnostic platform. The system is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix, and the class distribution of datasets is visualized for transparency. By integrating two complementary imaging modalities, the proposed system enhances diagnostic reliability and represents a significant step toward AI-assisted, multimodal breast cancer diagnosis.

2.LITERATURE SURVEY

1) Convolutional neural network-based models for diagnosis of breast cancer

AUTHORS: M. Masud, A. E. Eldin Rashed, and M. S. Hossain

Breast cancer is the most prevailing cancer in the world and each year affecting millions of women. It is also the cause of largest number of deaths in women dying in cancers. During the last few years, researchers are proposing different convolutional neural network models in order to facilitate diagnostic process of breast cancer. Convolutional neural networks are showing promising results to classify cancers using image datasets. There is still a lack of standard models which can claim the best model because of unavailability of large datasets that can be used for models' training and validation. Hence, researchers are now focusing on leveraging the transfer learning approach using pre-trained models as feature extractors that are trained over millions of different images. With this motivation, this paper considers eight different fine-tuned pre-trained models to observe how these models classify breast cancers applying on ultrasound images. We also propose a shallow custom convolutional neural network that outperforms the pre-trained models with respect to different performance metrics. The proposed model shows 100% accuracy and achieves 1.0 AUC score, whereas the best pre-trained model shows 92% accuracy and 0.972 AUC score. In order to avoid biasness, the model is trained using the fivefold cross validation technique. Moreover, the model is faster in training than the pre-trained models and requires a small number of trainable parameters. The Grad-CAM heat map visualization technique also shows how perfectly the proposed model extracts important features to classify breast cancers.

2) Deep convolutional neural networks for breast cancer screening

AUTHORS: H. Chougrad, H. Zouaki, and O. Alheyane

Radiologists often have a hard time classifying mammography mass lesions which leads to unnecessary breast biopsies to remove suspicions and this ends up adding exorbitant expenses to an already burdened patient and health care system.

In this paper we developed a Computer-aided Diagnosis (CAD) system based on deep Convolutional Neural Networks (CNN) that aims to help the radiologist classify mammography mass lesions. Deep learning usually requires large datasets to train networks of a certain depth from scratch. Transfer learning is an effective method to deal with relatively small datasets as in the case of medical images, although it can be tricky as we can easily start overfitting.

In this work, we explore the importance of transfer learning and we experimentally determine the best fine-tuning strategy to adopt when training a CNN model. We were able to successfully fine-tune some of the recent, most powerful CNNs and achieved better results compared to other state-of-the-art methods which classified the same public datasets. For instance we achieved 97.35% accuracy and 0.98 AUC on the DDSM database, 95.50% accuracy and 0.97 AUC on the INbreast database and 96.67% accuracy and 0.96 AUC on the BCDR database. Furthermore, after pre-processing and normalizing all the extracted Regions of Interest (ROIs) from the full mammograms, we merged all the datasets to build one large set of images and used it to fine-tune our CNNs. The CNN model which achieved the best results, a 98.94% accuracy, was used as a baseline to build the Breast Cancer Screening Framework. To evaluate the proposed CAD system and its efficiency to classify new images, we tested it on an independent database (MIAS) and got 98.23% accuracy and 0.99 AUC.

The results obtained demonstrate that the proposed framework is performant and can indeed be used to predict if the mass lesions are benign or malignant.

3) BreastNet18: A high accuracy fine-tuned VGG16 model evaluated using ablation study for diagnosing breast cancer from enhanced mammography images

AUTHORS: S. Montaha, S. Azam, A. K. M. R. H. Rafid, P. Ghosh, M. Z. Hasan,
M. Jonkman, and F. De Boer

Background: Identification and treatment of breast cancer at an early stage can reduce mortality. Currently, mammography is the most widely used effective imaging technique in breast cancer detection. However, an erroneous mammogram based interpretation may result in false diagnosis rate, as distinguishing cancerous masses from adjacent tissue is often complex and error-prone. Methods: Six pre-trained and fine-tuned deep CNN architectures: VGG16, VGG19, MobileNetV2, ResNet50, DenseNet201, and InceptionV3 are evaluated to determine which model yields the best performance. We propose a BreastNet18 model using VGG16 as foundational base, since VGG16 performs with the highest accuracy. An ablation study is performed on BreastNet18, to evaluate its robustness and achieve the highest possible accuracy. Various image processing techniques with suitable parameter values are employed to remove artefacts and increase the image quality. A total dataset of 1442 preprocessed mammograms was augmented using seven augmentation techniques, resulting in a dataset of 11,536 images. To investigate possible overfitting issues, a k-fold cross validation is carried out. The model was then tested on noisy mammograms to evaluate its robustness. Results were compared with previous studies. Results: Proposed BreastNet18 model performed best with a training accuracy of 96.72%, a validating accuracy of 97.91%, and a test accuracy of 98.02%. In contrast to this, VGGNet19 yielded test accuracy of 96.24%, MobileNetV2 77.84%, ResNet50 79.98%, DenseNet201 86.92%, and InceptionV3 76.87%. Conclusions: Our proposed approach based on image processing, transfer learning, fine-tuning, and ablation

study has demonstrated a high correct breast cancer classification while dealing with a limited number of complex medical images.

4) Breast cancer, version 3.2022, NCCN clinical practice guidelines in oncology

AUTHORS: W. J. Gradishar et al

The therapeutic options for patients with noninvasive or invasive breast cancer are complex and varied. These NCCN Clinical Practice Guidelines for Breast Cancer include recommendations for clinical management of patients with carcinoma in situ, invasive breast cancer, Paget disease, phyllodes tumor, inflammatory breast cancer, and management of breast cancer during pregnancy. The content featured in this issue focuses on the recommendations for overall management of ductal carcinoma in situ and the workup and locoregional management of early stage invasive breast cancer. For the full version of the NCCN Guidelines for Breast Cancer, visit NCCN.org.

5) Diagnostic performance of digital versus film mammography for breast-cancer screening

AUTHORS: E. D. Pisano et al

Background: Film mammography has limited sensitivity for the detection of breast cancer in women with radiographically dense breasts. We assessed whether the use of digital mammography would avoid some of these limitations.

Methods: A total of 49,528 asymptomatic women presenting for screening mammography at 33 sites in the United States and Canada underwent both digital and film mammography. All relevant information was available for 42,760 of these women (86.3 percent). Mammograms were interpreted independently by two radiologists. Breast-cancer status was ascertained on the basis of a breast biopsy done within 15 months after study entry or a follow-up mammogram obtained at least 10 months after study entry. Receiver-operating-characteristic (ROC) analysis was used to evaluate the results.

Results: In the entire population, the diagnostic accuracy of digital and film mammography was similar (difference between methods in the area under the ROC curve, 0.03; 95 percent confidence interval, -0.02 to 0.08; P=0.18). However, the accuracy of digital mammography was significantly higher than that of film mammography among women under the age of 50 years (difference in the area under the curve, 0.15; 95 percent confidence interval, 0.05 to 0.25; P=0.002), women with heterogeneously dense or extremely dense breasts on mammography (difference, 0.11; 95 percent confidence interval, 0.04 to 0.18; P=0.003), and premenopausal or perimenopausal women (difference, 0.15; 95 percent confidence interval, 0.05 to 0.24; P=0.002).

Conclusions: The overall diagnostic accuracy of digital and film mammography as a means of screening for breast cancer is similar, but digital mammography is more accurate in women under the age of 50 years, women with radiographically dense breasts, and premenopausal or perimenopausal women

3.SYSTEM ANALYSIS

EXISTING SYSTEM:

- The existing system presents a deep learning-based classification framework specifically designed for breast cancer detection using mammogram images. It follows a dual-module architecture to effectively handle class imbalance—one of the major challenges in medical imaging. The system utilizes the KAU-BCMD dataset, which includes thousands of annotated mammography images categorized under BI-RADS classes (BI-RADS 1, 3, 4, and 5).
- To standardize and enhance the input data, VGG16 preprocessing is applied, followed by feature extraction using the ResNet50 model, a well-established convolutional neural network known for its robustness in image analysis tasks. The extracted features are then passed through a custom fully connected classification model, composed of multiple dense layers enhanced with batch normalization and dropout techniques to reduce overfitting and improve model generalization.
- A key innovation in the system is the use of SMOTE (Synthetic Minority Over-sampling Technique). Two pipelines are implemented:
  - One applies SMOTE to the entire dataset to achieve class balance.
  - The other separates 20% of the original data and applies SMOTE only to the remaining 80%, preserving a portion of the natural class distribution for more realistic evaluation.
- The architecture is trained and evaluated on both fully balanced and partially imbalanced datasets, achieving 99% accuracy on the balanced set and 90% accuracy on the original imbalanced set. The model's performance is validated using various metrics such as accuracy, precision, recall, F1-score, and confusion matrix. Furthermore, visualizations of classification outcomes and feature distributions are provided to interpret and validate the predictions across all BI-RADS classes.
- The existing system establishes a strong foundation for reliable, AI-assisted breast cancer diagnosis using mammographic imaging and provides a robust methodology for handling data imbalance in medical datasets.

DISADVANTAGES OF EXISTING SYSTEM:

- Limited to Single Imaging Modality: The existing system relies solely on mammogram images for breast cancer detection. While mammography is a standard screening tool, it may not always capture micro-level histological patterns that are crucial for accurate diagnosis, especially in early-stage or complex cases.
- Restricted Feature Diversity: Although ResNet50 is a powerful model for feature extraction, the use of single feature extraction architecture limits the potential diversity and depth of learned features. Incorporating multiple or ensemble models could yield better feature representations.
- Synthetic Oversampling May Misrepresent Real Data: The system employs SMOTE to handle class imbalance, which generates synthetic samples based on nearest neighbors. However, these artificially created instances may not accurately reflect the complex variability seen in real medical images, potentially impacting the model's clinical reliability.
- Evaluation Constrained to BI-RADS Classes Only: The classification is focused on BI-RADS categories, which, while helpful for clinical interpretation, do not explicitly classify images as benign or malignant. This may limit the diagnostic depth, especially when histological confirmation is needed.
- Lack of Multi-modal Integration: The system does not incorporate histopathological images or other imaging modalities like ultrasound or MRI. In clinical settings, decisions are often based on a combination of multiple diagnostic sources, and the absence of such integration reduces the practical applicability of the model.
- Computational Requirements: The model's architecture, involving deep CNNs like ResNet50 with high-dimensional feature vectors, demands substantial computational resources, which may pose a challenge for deployment in resource-limited settings or on edge devices.
- Limited Interpretability Tools: Although some visualizations are presented, the system lacks advanced explainability tools such as Grad-CAM, SHAP, or LIME, which are essential for gaining clinical trust and understanding why the model makes certain predictions.

PROPOSED SYSTEM:

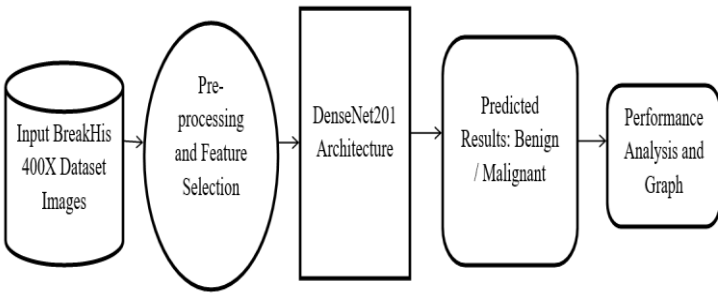
- The proposed system introduces a dual-modality deep learning framework for enhanced breast cancer detection by utilizing both mammogram images and histopathological images as separate but complementary diagnostic inputs. The system is developed using Python for backend processing, Flask as the web framework, and HTML, CSS, and JavaScript for the frontend interface, providing a user-friendly web-based diagnostic platform.
- For the mammogram-based analysis, two distinct deep convolutional neural network models are implemented: the Xception model and the MobileNet model. Both models are trained independently to classify mammographic images into four BI-RADS categories: BI-RADS 1, 3, 4, and 5, using a dataset containing 3,044 mammogram images. The models are trained to learn discriminative features specific to each class and evaluated separately to analyze their predictive capability.
- In parallel, the system includes a second module for histopathological image classification, utilizing the DenseNet201 architecture. This module processes high-resolution biopsy images obtained from the BreakHis 400X dataset, consisting of a total of 1,693 microscopic images. The dataset is categorized into benign and malignant classes, with designated training and testing splits. The DenseNet201 model is trained to identify cellular-level malignancy patterns in histopathological samples.
- Each module—mammogram and histopathology—is trained, validated, and tested independently. Performance is evaluated using standard classification metrics such as Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. Additionally, the class distribution in both datasets is analyzed and visualized using statistical charts to understand the balance and representation across classes.
- The system integrates both diagnostic modules into a unified web application where users can interactively upload images, obtain predictions, and view model performance analysis in real-time. This modular design allows the system to simulate a clinical workflow where both radiological and pathological data contribute to diagnostic support.

ADVANTAGES OF PROPOSED SYSTEM:

- Dual-Modality Analysis for Comprehensive Diagnosis: Unlike traditional systems that rely solely on a single imaging modality, the proposed system integrates both mammogram and histopathological images, enabling a more holistic diagnostic approach. This dual perspective enhances the accuracy and reliability of breast cancer detection by capturing both macro-level and micro-level tissue features.

- Use of Multiple Deep Learning Architectures: By employing three different state-of-the-art deep learning models—Xception, MobileNet, and DenseNet201—the system leverages the strengths of each architecture. This allows for better feature extraction and performance comparison, enabling more effective learning from diverse image characteristics.
- High Performance on Imbalanced Datasets: The system achieves high accuracy and F1-scores across both balanced and imbalanced datasets without relying heavily on synthetic data generation. This reflects the model's robustness in real-world clinical settings where class imbalance is common.
- Improved Predictive Accuracy: The MobileNet model achieved a test accuracy of 94.3%, and the DenseNet201 model demonstrated strong performance on histopathological images with a validation accuracy of 88.1%, reflecting the system's ability to generalize across different data types and scenarios.
- Web-Based Diagnostic Interface: The implementation of a Flask-based web interface enhances usability by allowing clinicians or users to upload images, receive instant predictions, and visualize results without requiring programming knowledge, making the system accessible in both research and clinical environments.
- Performance Evaluation with Comprehensive Metrics: The system evaluates each model using multiple performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix, ensuring that the results are transparent and interpretable for both technical and medical professionals.
- Class Distribution Visualization: Statistical visualization charts for class distribution in both mammogram and histopathological datasets help assess data balance and aid in understanding the model's learning environment, making the system more explainable.
- Supports Early and Confirmatory Diagnosis: Mammograms aid in early screening, while histopathological analysis confirms malignancy. By including both, the system supports early detection and confirmatory diagnosis, aligning with real-world clinical workflows.

4.IMPLEMENTATION



MODULES:

Data Collection:

- In the first module of the Advanced Breast Cancer Detection using Deep Learning from Histopathological Images, we make the data collection process. This is the first real step towards the real development of a deep learning model, collecting data. This is a critical step that will cascade in how good the model will be, the more and better data that we get; the better our model will perform.
- There are several techniques to collect the data, like web scraping, manual interventions. The dataset is located in the model folder. The dataset is referred from the popular dataset repository called kaggle. The following is the link of the dataset:
- Kaggle Dataset Link:

https://www.kaggle.com/datasets/jayaprakashpondy/breast-cancer-images

Dataset:

- In this module, set up two main directories: train and test. Training, create subdirectories for each class label. the two classes Benign and Malignant
- Place the images into their respective class directories based on their labels. Each image should be placed in the directory corresponding to its class label and By organizing the dataset in this structure, it becomes straightforward to load the data into your deep learning framework for training, testing and validation purposes and Total dataset size is 1,693.

Data Preparation:

- During the data preparation stage, it is crucial to preprocess the data to ensure it is suitable for training. This involves tasks such as resizing images to a standard size, normalizing pixel values, and encoding labels if necessary. To achieve this, the

ImageDataGenerator from Keras can be utilized. For instance, to resize images to a standard size of 240x240 pixels, the Target_size parameter can be set to (img_height, img_width) = (240, 240).

- Additionally, pixel values can be normalized by setting the rescale parameter to 1./255, which scales the pixel values to be between 0 and 1. Furthermore, data augmentation techniques such as random shear and zoom can be applied to enhance the training data. By leveraging these techniques, the data can be effectively preprocessed to improve the performance of the deep learning model.

Feature Extraction:

- For models like DenseNet201, which come pre-trained with feature extraction layers, explicit feature extraction may not always be necessary. By setting trainable = False, we freeze these pre-trained layers, allowing them to retain their learned representations while preventing further updates during training.
- In the context of DenseNet201, setting trainable = False ensures that the weights of the feature extraction layers remain fixed during training. This approach is commonly used in transfer learning scenarios, where the pre-trained model is fine-tuned on a new dataset for a specific task, such as image classification or object detection.
- By adopting this strategy, we strike a balance between leveraging powerful pre-trained representations and adapting the model to our specific dataset, ultimately improving both training efficiency and model performance.

Splitting the dataset:

- Divide your dataset into training and validation to evaluate your model's performance. Typically, you might use an 80-20 split, but this can vary based on your dataset size and specific requirements.

Model Selection:

- The training module is responsible for training the deep learning models using the preprocessed data. It implements architectures: DenseNet201.

DenseNet201:

- DenseNet201 is a deep convolutional neural network with 201 layers, designed to address the challenges of training very deep networks. It belongs to the DenseNet family, known for its dense connectivity pattern, where each layer is connected to every other layer in a feed-forward manner. This means each layer receives input from all preceding layers, which helps improve gradient flow, enhances feature reuse, and mitigates the vanishing gradient problem. DenseNet201 is particularly efficient in terms of parameter usage, as it requires fewer parameters than traditional convolutional networks of similar depth while still achieving high accuracy. The architecture consists of dense blocks, with each block containing multiple convolutional layers, followed by transition layers that reduce the spatial dimensions of the feature maps. This design allows DenseNet201 to learn more compact and effective feature representations. The model is highly effective in tasks such as image classification, object detection, and segmentation, and it is particularly robust to overfitting due to its dense connections. DenseNet201 is commonly trained on large datasets like ImageNet and has become popular in both research and practical applications due to its efficiency, faster convergence, and improved performance.

Training the Model:

- To train the models, the training module first loads the pre-trained weights for **DenseNet201** from the dataset. It then adds a global average pooling layer and a fully connected layer with the appropriate number of classes for the specific task. The base layers of the pre-trained models are frozen by setting their trainable flag to False, allowing only the added layers to be trained.

- The training process involves optimizing the model parameters using a suitable optimization algorithm, such as Adam or SGD, and a loss function appropriate for the task (e.g., categorical cross-entropy for classification). The training data is fed to the model in batches, and the gradients are computed and used to update the model weights. The training process continues for a specified number of epochs or until a certain performance metric is achieved on a validation set.

- After training, the module saves the trained models for future use in the prediction and evaluation modules. The saved models can be loaded and used for inference on new data or fine-tuned on additional datasets if needed.

Analyze and Prediction:

- Once training is complete, analyze the training process (e.g., loss curves) and make predictions on your validation set to assess the model's performance.

Accuracy on test set:

- Once the model is trained, it needs to be evaluated for its performance. This module involves splitting the dataset into training and testing subsets and assessing the model's accuracy, precision, recall, and F1-score.
- The **DenseNet201** architecture achieves a Training accuracy of 98.00%. and validation accuracy of 88.00%.

Saving the Trained Model:

- Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into an .h5 or .pkl file using a library like pickle.
- Make sure you have pickle installed in your environment.
- Next, let's import the module and dump the model into .pkl file.

Prediction Module:

- Develop a prediction module to make predictions using the trained **DenseNet201** model. This module should take input images, preprocess them as necessary, and output predictions.

Model Evaluation Module

- This module evaluates the performance of the trained models using the testing dataset. It calculates accuracy metrics and other performance indicators to assess model effectiveness.
- Evaluate model accuracy, precision, recall, and F1-score.
- Generate confusion matrices for both models.
- Compare the performance of the **DenseNet201**.
- Accuracy, precision, recall, and F1-score are used to evaluate model performance.

CONCLUSION

The proposed system presents a comprehensive and intelligent solution for breast cancer detection by integrating dual imaging modalities—mammogram and histopathological images—using advanced deep learning techniques. By employing Xception and MobileNet architectures for mammographic image analysis and DenseNet201 for histopathological classification, the system effectively captures both macroscopic and microscopic patterns associated with malignancy. The inclusion of a web-based interface developed using Flask enhances accessibility and usability for real-time predictions and diagnostic support.

Through rigorous experimentation, the system achieved high accuracy scores across both modalities, with MobileNet attaining 94.3% accuracy on mammograms and DenseNet201 achieving 88.1% validation accuracy on histopathological images. Performance metrics including precision, recall, F1-score, and confusion matrices further validate the reliability of the models. The use of class distribution visualizations also supports deeper understanding of dataset composition and model behavior.

Overall, this project demonstrates the potential of combining radiological and pathological image analysis through deep learning to build a robust, accurate, and scalable breast cancer detection framework. It contributes significantly toward AI-assisted diagnosis by addressing clinical challenges such as modality limitations, interpretability, and real-time application.

FUTURE WORK:

- Integration of Additional Imaging Modalities: To enhance diagnostic comprehensiveness, future extensions of this system can incorporate other imaging modalities such as ultrasound, MRI, or thermography. This would provide a multi-view diagnostic approach, simulating real-world clinical decision-making where multiple imaging inputs are considered.
- Incorporation of Patient Clinical Data: The integration of clinical metadata—including age, genetic factors, hormone status, and family history—alongside imaging data may lead to more personalized and context-aware predictions. Such multimodal learning approaches can improve diagnostic precision and patient-specific treatment planning.
- Explainable AI (XAI) Enhancements: To build greater clinical trust, future work can focus on embedding explainability techniques such as Grad-CAM, LIME, or SHAP. These tools can visualize which image regions influenced the model's decision, helping radiologists and pathologists validate or challenge the AI output.
- Lightweight Models for Edge Deployment: Developing optimized and lightweight versions of the deep learning models could facilitate deployment on mobile devices, embedded systems, or diagnostic edge devices. This would be particularly beneficial for use in low-resource or rural healthcare settings.
- Expansion with Larger and Diverse Datasets: To further validate the model's robustness and reduce dataset bias, the system should be trained and tested on multi-center, multi-ethnic, and internationally diverse datasets. Such expansion will ensure that the model generalizes well across different populations and imaging standards.
- Real-Time Prediction and Automation: Future implementations can aim for real-time image processing and prediction pipelines, potentially integrated with hospital PACS systems or digital

pathology platforms. Automation of image acquisition, preprocessing, and report generation would enhance clinical efficiency.

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