BREAST CANCER CLASSIFICATION WITH TRANSFER LEARNING

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BONAFIDE CERTIFICATE

Certified that this Minor Project Report titled "**Breast Cancer Classification with Transfer Learning**" is the bonafide work done by **N. SRAVAN KUMAR (RA2111047010189), K. AVINASH REDDY (RA2111047010201), C. GOKUL KRISHNA REDDY (RA2111047010190)** of III Year/ V Sem B.Tech (AI) who carried out under my supervision for the course 18AIC301J – Deep Learning Techniques. Certified further, that to the best of my knowledge the work reported herein does not form part of any other work.

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ABSTRACT

Breast cancer remains a significant global health challenge, necessitating innovative approaches for early and accurate diagnosis. This project focuses on Breast Cancer Classification with Transfer Learning, employing advanced deep learning techniques to enhance diagnostic accuracy and efficiency. The study begins with an overview of the objectives, motivated by the urgent need for improved breast cancer detection. Leveraging transfer learning, we harness the power of pre-trained neural networks, specifically ResNet, for more effective classification.

A comprehensive methodology section details the data collection, pre-processing, model architecture, training, and evaluation procedures. Experimental results demonstrate the potential for superior accuracy and precision in breast cancer diagnosis. By utilizing modern tools and frameworks, such as Python, TensorFlow, and GPUs, we showcase the feasibility of this approach in clinical practice. The societal benefits of this research include early cancer detection, reduced misdiagnosis, and cost and time savings, emphasizing its potential to revolutionize breast cancer diagnosis and treatment.

In this research, we employ well-established pre-trained models such as VGG16, MobileNet, and ResNet to extract intricate features from breast cancer histopathological images. By fine-tuning these models on a targeted dataset, we harness their ability to discern subtle patterns indicative of benign and malignant tissues. The study involves the preprocessing of medical images, data augmentation to augment the limited dataset, and the integration of transfer learning techniques into the model architecture. The analysis of identified patterns in benign and malignant tumor classification shed light on the interpretability of the models. Understanding the specific types of images that pose challenges to the models is crucial for refining their performance.

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ABBREVIATIONS

BreaKHis:	**Breast cancer histopathological image classification**
BACH:	**Breast cancer histology images**
CNN:	**Convolutional neural network**
DenseNet:	**Dense convolutional Network**
ResNet:	**Residual network**
VGG:	**Visual Geometry Group**
SVM:	**Support vector machine**
BN:	**Batch normalization**
ReLU:	**Rectifie d linear unit**
ROC:	**Receiver operating characteristic**
AUC:	**Area under the ROC curve**
ACC:	**Accuracy**

INTRODUCTION

1.1 Introduction

Breast cancer is a pervasive and life-altering disease that affects millions of individuals worldwide. Early detection and accurate diagnosis are pivotal factors in improving survival rates and treatment outcomes. Traditional methods for breast cancer classification have shown promise, but they are constantly evolving with the integration of cutting-edge technologies.

In this project, we explore the realm of breast cancer classification with Transfer Learning, a powerful machine learning technique that harnesses pre-trained neural networks to enhance the accuracy and efficiency of the diagnostic process. The motivation behind this research stems from the need to address the ever-increasing demand for more effective and timely breast cancer diagnosis.

Transfer learning offers a promising avenue for improving breast cancer classification, as it leverages knowledge acquired from vast datasets in unrelated domains, reducing the requirement for large volumes of specific medical data. By adapting deep learning models like ResNet to the domain of medical imaging, we aim to create a robust classification system capable of detecting breast cancer with remarkable precision.

Many researchers have proposed numerous strategies for the automatic classification of cells in breast cancer detection in recent decades. By identifying nucleus traits, cancerous cells of breast cancer can be classified as benign and malignant. However, the system's efficiency and accuracy decrease as a result of the complexity of typical machine learning procedures such as pre-processing, segmentation, feature extraction, and others. Traditional ML problems can be solved using the recently developed DL technique. With exceptional feature representation, this technique can perform picture classification and object localization challenges. The transfer learning approach used a natural-image dataset such as ImageNet and then applied a fine-tuning technique to solve this problem. The main benefit of transfer learning is that it improves classification accuracy and speeds up the training process.

1.2 Problem Statement

Breast cancer is a widespread and life-threatening disease affecting millions of individuals worldwide. Early detection and accurate diagnosis are critical for effective treatment and improved survival rates. Transfer learning, a technique where a pre-trained model is fine-tuned on a specific task, has proven to be highly effective in various computer vision applications.

1.3 Software Requirements Specification

The breast cancer classification system will involve the development of real-time image classification. The system will provide predictions based on a trained model. The input will be an image of type JPEG, PNG and GIF. Then the system supports batch processing for multiple breast cancer images. Classification results (benign/malignant) are displayed under Output.

Design and Implementation Constraints

- The system will be developed using Python for its rich ecosystem of Deep Learning libraries.
- The classification models like CNN and image models are used as architecture. Transfer Learning models like VGG16, ResNet, MobileNet are some pre-trained models are used for training of current Model.

Usability and Maintainability Requirements

- The Model usage is easy and user- friendly and user will get clear guidance from the errors.
- The codebase should be well-documented for ease of maintenance.
- Updates to the model or system should be seamless and not disrupt normal operation.

Legal and Ethical Requirements

- The system should comply with data protection regulations and ethical standards for handling medical data.

This Software Requirements Specification outlines the features, functionalities, and constraints for the development of the Breast Cancer Classification System with Transfer Learning. It serves as a comprehensive guide for stakeholders involved in the system's design, development, and testing.

LITERATURE SURVEY

2.1 Literature Review

Around 1.7 million women were diagnosed with cancer in 2012. Breast cancer is the most frequent type of cancer worldwide. Risk factors for breast cancer include age, family history, and previous health problems [1]. Women account for the lion's share of cancer deaths; annually, an estimated 2.1 million people are diagnosed with breast cancer. Recent research estimates that 627 thousand women lost their lives to cancer in 2018, accounting for fifteen percent of all cancer deaths in women [2]. It is usual practice to use a deep learning-based model for breast cancer diagnosis and classification when using computer visualization. Clinicians face difficulties in making a cancer diagnosis from mammography scans due to the complexity of early breast cancer and the fading of images. That is why it is so important to enhance a doctor's detection efficiency with the help of deep learning algorithms used in the CAD system.

To categorize breast cancer, the authors of [1] proposed a convolutional neural network (CNN) based framework for analysing mammography images. In the beginning, preprocessing was carried out so the mammography images could be seen. Then, the deep learning model that was used to extract the features was trained using the pre-processed images. SoftMax, a CNN classifier, was then used to categorize the last layer's retrieved features. The preferred model enhanced the introduced framework's classification accuracy of mammography images. Accuracy values of 0.8585 and 0.8271 for the proposed framework demonstrate its superiority to those of the state-of-the-art alternatives.

The authors of [3] revealed early results for utilizing transfer learning to identify breast abnormalities likely to progress to cancer. After testing numerous deep learning models, they settled on ResNet50 and MobileNet as the best options. Both models achieved the highest accuracy levels (78.4% and 74.3%, respectively). They used several preprocessing methods to enhance the accuracy of the categorization further. Last but not least, in, researchers introduced a novel hybrid processing approach that combines principal component analysis (PCA) and logistic regression (LR).

First-order local entropy, a texture-based technique, segmented the tumour patches. Malignancy indicators such as radius and area were derived using the feature extraction findings. Results from applying this strategy indicated that the CC and MLO views were 88% and 80% accurate at detecting breast cancer, respectively. Tumour identification with thresholding and CNN methods were the primary focus of the previous research, along with information fusion, hyperparameter value selection by hand, data enhancement, and manual hyperparameter tuning.

VGG [4] is easy to implement but slow to train. Nowadays, many deep-learning-based methods are implemented on influential backbone networks; among them, both DenseNet and ResNet [5] are very popular. Due to the longer path between the input layer and the output layer, the information vanishes before reaching its destination. DenseNet was developed to minimize this effect. The key base element of ResNet [5] is the residual block. DenseNet concentrates on making the deep learning networks move even deeper as well as simultaneously making them well organized to train by applying shorter connections among layers. In short, ResNet [5] adopts summation, whereas DenseNet deals with concatenation.

Related Works:

Title	Author	Description
Deep Learning-Based Classification of Breast Tumors with Transfer Learning" (2019)	S. U. Akram, M. Khalid, and M. A. R. Malik	The study investigates the use of transfer learning with pre-trained CNNs for the classification of breast tumors using histopathological images.
Transfer Learning for Improved Convolutional Neural Network-Based Mammogram Classification" (2018)	H. A. Alshazly, M. A. B. Lin, and Y. A. E. M. Elfadly	This study explores the application of transfer learning using pre-trained CNN models, such as VGG16 and ResNet, for mammogram, classification.
Deep Learning for Breast Cancer Histopathological Image Analysis: A Comprehensive Study" (2020)	A. Rakhlin, A. Shvets, A. Iglovikov, and A. Kalinin	This study provides a comprehensive exploration of deep learning methods, including transfer learning, for breast cancer histopathological image analysis.
Imbalanced Breast Cancer Classification Using Transfer Learning	Singh R, Ahmed T, Kumar A, Singh AK, Pandey AK, Singh SK	This study proposed a framework based on the notion of transfer learning to address cancer issue and focus our efforts on histopathological and imbalanced image classification.

Table. 1. Related Works and Articles

SYSTEM ARCHITECTURE AND DESIGN

3.1 Architectures of Implemented Models

VGG16 Architecture:

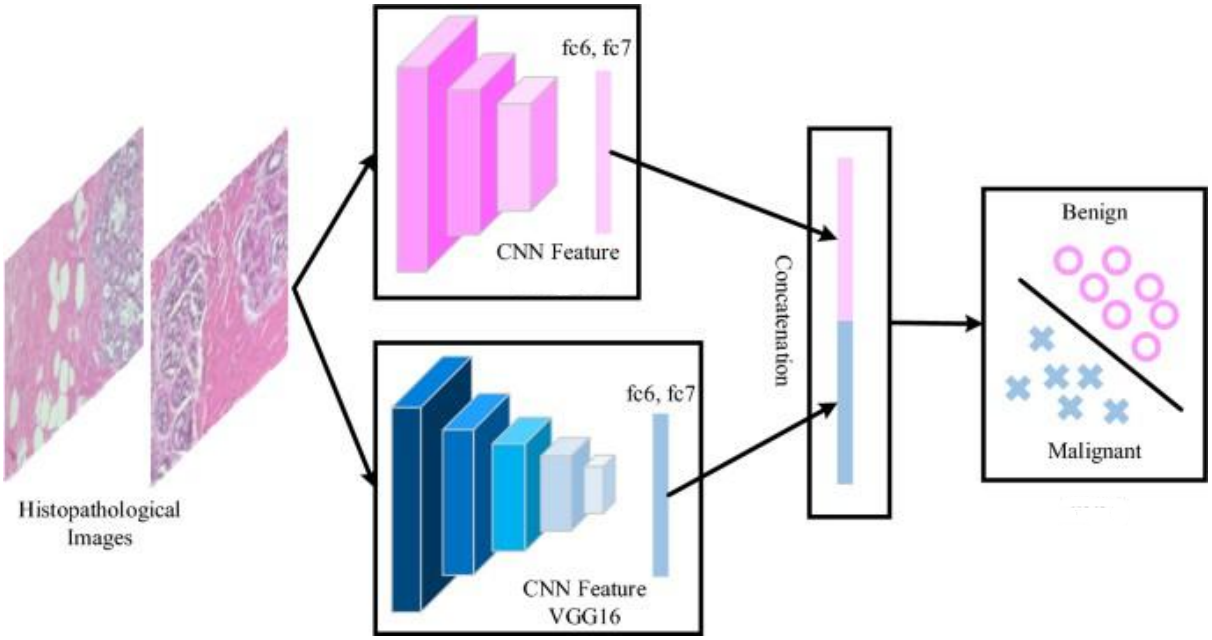

Fig. 1. VGG16 with CNN Architecture

The VGG16 architecture is a popular convolutional neural network (CNN) architecture known for its deep structure and strong performance on image classification tasks. Transfer learning involves using a pre-trained model on a large dataset for a specific task and then fine-tuning it for a new task. In the context of breast cancer classification, you can use a pre-trained VGG16 model for feature extraction and then train additional layers for the specific task of distinguishing between benign and malignant breast cancer.

MobileNetV3 Architecture:

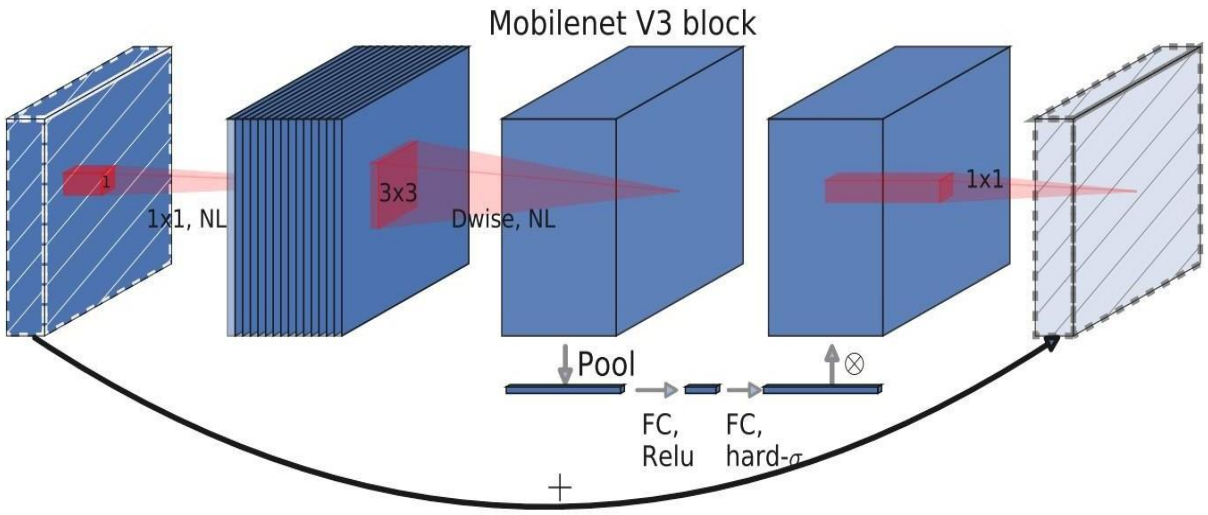

Fig. 2. MobileNetV3 Architecture blocks of Residual Layer

When adapting MobileNetV3 for breast cancer classification with transfer learning, you can leverage a pre-trained MobileNetV3 model and fine-tune it on your specific dataset. Below is an overview of how you can use MobileNetV3 for this purpose:

1. Overview of MobileNetV3 Architecture:

MobileNetV3 introduces several key features, including:

- **Inverted Residuals with Linear Bottlenecks:** This structure helps maintain low latency and improves information flow through the network.
- **MobileNetV3 Blocks:** It includes multiple types of blocks, such as MobileNetV3 Small, MobileNetV3 Large, and MobileNetV3 EdgeTPU, each with variations in the number of layers and parameters to balance speed and accuracy.
- **Squeeze-and-Excitation (SE) Blocks:** These blocks help the model focus on important features by adaptively recalibrating channel-wise feature responses.
- **Hard-swish Activation Function:** It is a non-linear activation function that is computationally efficient and maintains a good trade-off between accuracy and speed.

ResNet Architecture:

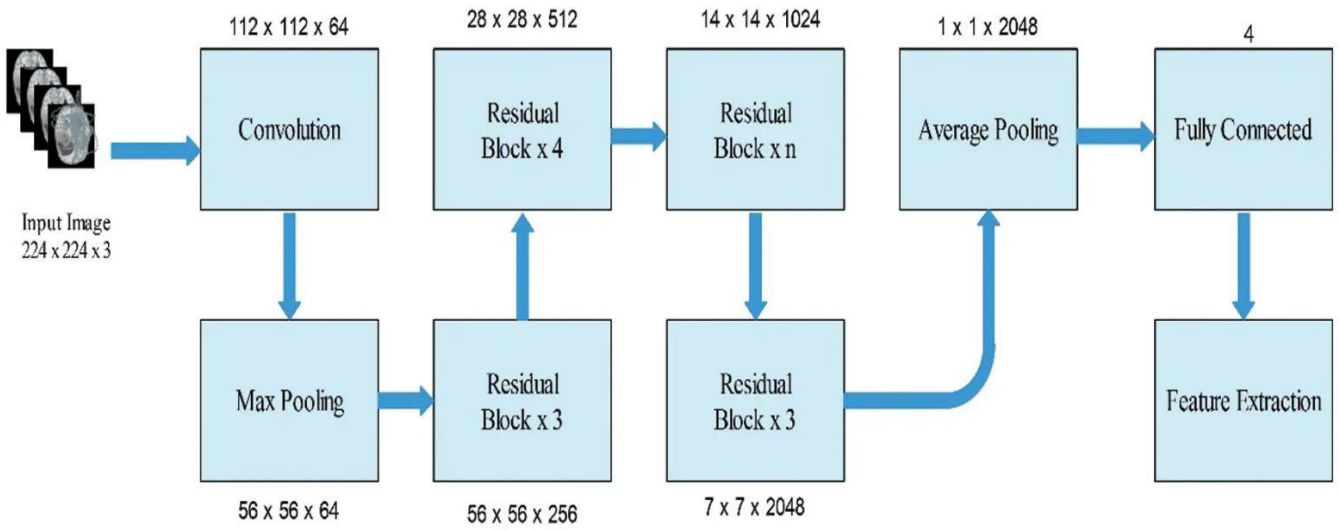

Fig. 3. Modified ResNet50 model for breast cancer classification

The ResNet-50 architecture is a deep convolutional neural network (CNN) that belongs to the ResNet (Residual Network) family. ResNet-50 has 50 layers and is widely used for various computer vision tasks, including image classification. This adaptation of the ResNet-50 architecture allows you to leverage the powerful feature extraction capabilities learned from a large dataset (ImageNet) and fine-tune the model for breast cancer classification using a smaller, task-specific dataset. The transfer learning approach helps accelerate the training process and improves the model's ability to generalize to new data. Adjust the hyperparameters, such as learning rate and batch size, based on the characteristics of your breast cancer dataset.

3.2 Design of Modules

When designing the modules for a breast cancer classification system using transfer learning, you'll want to create a modular and organized structure to enhance maintainability, scalability, and collaboration.

1. Data Module:

- **Submodules:**
    - **Data Loader:** Handles the loading and preprocessing of breast cancer images from the dataset.
    - **Data Splitter:** Divides the dataset into training, validation, and test sets.
- **Responsibilities:**
    - Load and preprocess images.
    - Split the dataset for training and evaluation.

2. Model Module:

- **Submodules:**
    - **Base Model Loader:** Loads a pre-trained convolutional neural network (CNN) as the base model.
    - **Transfer Learning Layer Builder:** Constructs additional layers for breast cancer classification.
    - **Model Trainer:** Handles the training process.
    - **Model Evaluator:** Evaluates the model on test data.
- **Responsibilities:**
    - Load a pre-trained base model.
    - Build transfer learning layers.
    - Train and evaluate the model.

3. Utilities Module:

- **Submodules:**
    - **Image Processing Utilities:** Provides functions for image manipulation.
- **Responsibilities:**
    - Enhance code modularity and maintainability.

METHODOLOGY

4.1 Proposed Methodology

Building a breast cancer classification system with transfer learning involves several key steps, from data preparation to model training and evaluation. Below is a methodology outlining the major steps using popular pre-trained models like CNN, VGG16, ResNet50, and MobileNetV3. This methodology assumes the use of a deep learning framework such as TensorFlow or Keras.

1. Data Preparation:

1. **Data Collection:**
    - Gather a dataset of breast cancer histopathological images. Common datasets include BreakHis .
    - Ensure images are labeled as benign or malignant.
2. **Data Preprocessing:**
    - Resize images to a consistent input size suitable for the chosen pre-trained model.
    - Normalize pixel values to a standard range (e.g., [0, 1]).
    - Augment the dataset to increase its diversity (rotate, flip, zoom).

2. Model Selection:

1. **Choose Pre-trained Model:**
    - Consider models like VGG16, ResNet50, and MobileNetV3, which are known for their effectiveness in image classification tasks.
    - Evaluate the trade-offs between model complexity and accuracy.
2. **Transfer Learning:**
    - Remove the last classification layer(s) of the pre-trained model.
    - Add new layers for binary classification (benign or malignant).
    - Freeze the pre-trained layers to retain learned features.

3. Model Training:

1. **Data Splitting:**
    - Divide the dataset into training, validation, and test sets.

2. **Loss Function and Optimizer:**
    - Choose a suitable loss function (e.g., binary cross-entropy) and optimizer (e.g., Adam).
3. **Training:**
    - Train the model using the training set.
    - Monitor performance on the validation set to prevent overfitting.
    - Fine-tune hyperparameters as needed.
4. **Model Evaluation:**
    - Evaluate the trained model on the test set.
    - Assess performance using metrics like accuracy, precision, recall, F1 score, and confusion matrix.

4. Model Fine-tuning:

1. **Hyperparameter Tuning:**
    - Experiment with learning rates, batch sizes, and other hyperparameters to optimize performance.
2. **Transfer Learning Variations:**
    - Explore different strategies like feature extraction or fine-tuning different layers of the pre-trained model.

Compare Model Performances:

- If multiple pre-trained models were used, compare their performances on a validation or test set.
- Choose the model with the best performance for deployment.

Tools and Frameworks:

- Use TensorFlow or Keras for deep learning model development.
- Leverage Keras (integrated with TensorFlow) for ease of building and training models.
- Utilize popular Python libraries for data manipulation and visualization (NumPy, Pandas, Matplotlib).

4.2 Image Augmentation

Image augmentation is a crucial technique in breast cancer classification using deep learning models, enhancing the generalization capability of the model and mitigating overfitting. In the context of breast cancer histopathological images, image augmentation involves applying various transformations to the original images, creating diverse versions of the dataset for training. Common augmentations include random rotations, flips, zooms, and shifts, simulating different perspectives and orientations of breast tissue samples. By introducing these variations during training, the model becomes more robust to different image conditions, improving its ability to accurately classify unseen data. This is particularly essential in medical imaging, where datasets may be limited, and the diversity of pathological variations needs to be effectively captured.

In breast cancer classification, image augmentation contributes to the model's ability to learn invariant features, allowing it to discern relevant patterns across different orientations and scales. This technique helps prevent the model from memorizing specific characteristics of the training dataset while improving its sensitivity to diverse tissue structures indicative of benign or malignant conditions. As a result, the augmented dataset ensures that the trained model generalizes well to unseen pathology images, leading to more reliable and robust breast cancer classification models in real-world applications.

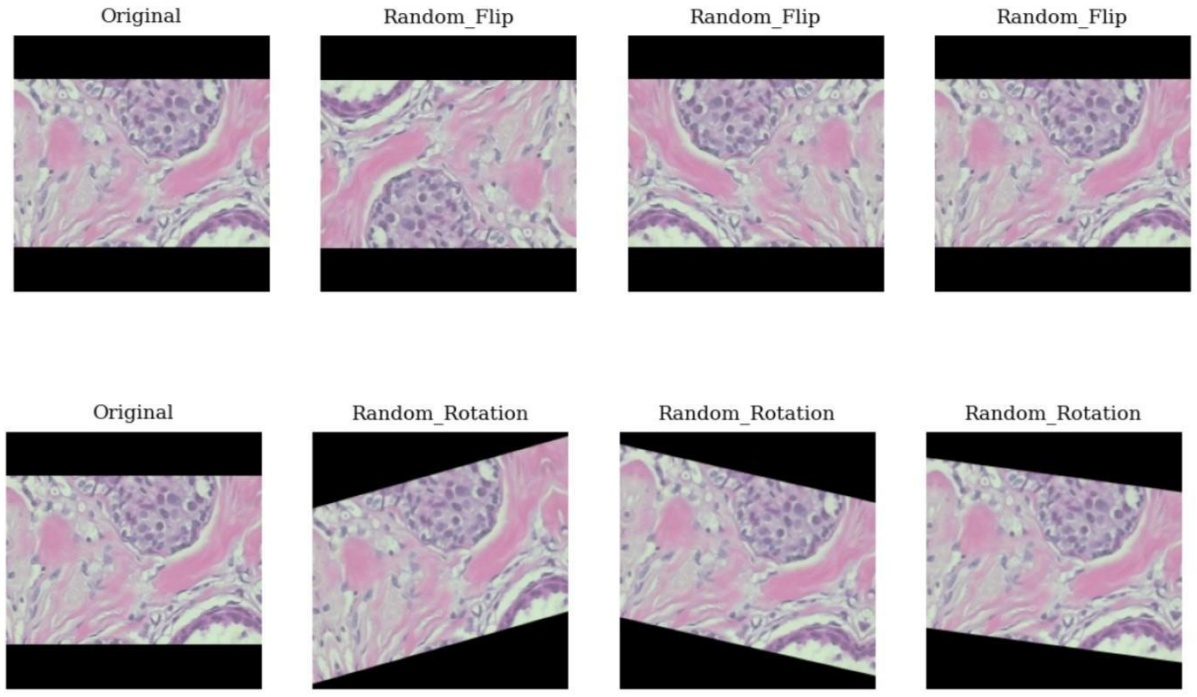

Fig. 4. Image Augmentation of Breast Cancer Data

4.3 Transfer Learning

Transfer learning is a powerful technique in breast cancer classification that leverages pre-trained neural network models on large datasets to boost the performance of a model trained on a smaller, domain-specific dataset. In the context of breast cancer, deep learning models such as Convolutional Neural Networks (CNNs) pre-trained on general image datasets, such as ImageNet, capture generic features like edges, textures, and shapes. By transferring this knowledge to a breast cancer classification task, the model can effectively learn to recognize subtle patterns indicative of benign or malignant tumors. This approach significantly reduces the need for large, annotated datasets for training, making it particularly advantageous in medical imaging applications where labeled data is often limited.

Transfer learning is especially beneficial for breast cancer classification due to the shared characteristics in various medical imaging datasets. Pre-trained models like VGG16, ResNet50, or MobileNetV3, which have excelled in general image classification tasks, can be fine-tuned on breast cancer images to learn specific features relevant to malignancy. The pre-trained model serves as a feature extractor, capturing hierarchical representations of visual information. By customizing the final layers for binary classification, the model can effectively discern between benign and malignant breast tissue, demonstrating the versatility and efficiency of transfer learning in enhancing the accuracy and generalization of breast cancer classification models.

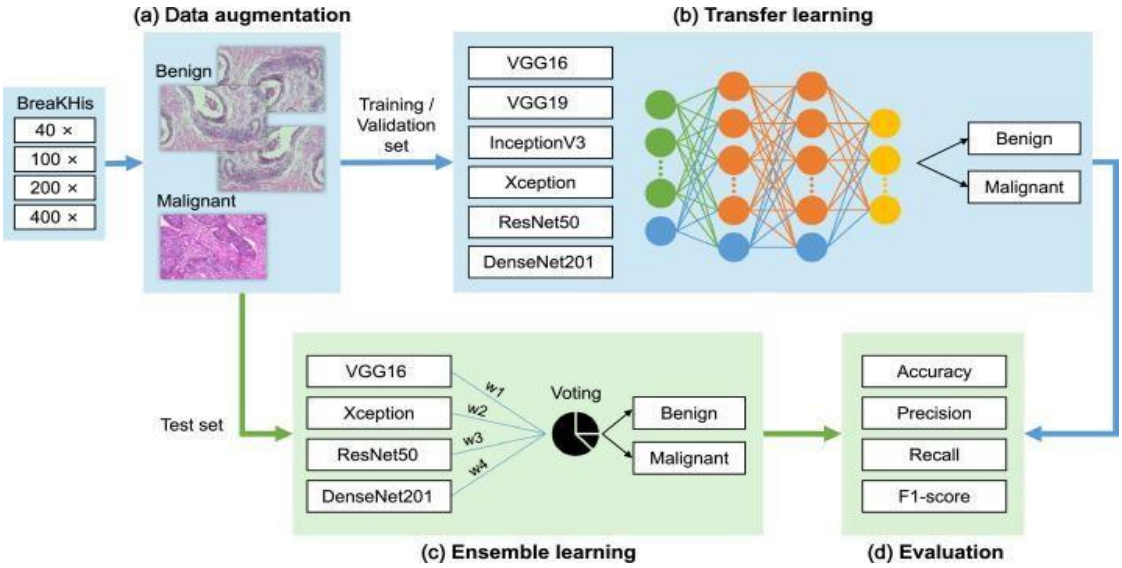

Fig. 5. Transfer Learning of pre- trained Models

CODING

Training and Validation Splitting:

```
X_train, X_valid, y_train, y_valid = train_test_split(train["filename"],
                                                      train["label"].map(classes),
random_state=SEED)
train_ds = tf.data.Dataset.from_tensor_slices((X_train, y_train))\
            .map(load_image).batch(BATCH_SIZE)
validation_ds = tf.data.Dataset.from_tensor_slices((X_valid, y_valid))\
            .map(load_image).batch(BATCH_SIZE)
```

Data Augmentation:

```
sample_image = load_image(*train[["filename", "label"]].iloc[0])[0]


def plot_augmentations(augmentation_layer: tf.keras.layers.Layer) -> None:
    augment_name = augmentation_layer.name
    fig, (ax0, *axes) = plt.subplots(ncols=4, figsize=(8, 4))
    ax0.imshow(sample_image.numpy().astype("uint8"))
    ax0.set_title("Original", size=10, pad=10)
    ax0.axis("off")
    for idx, ax in enumerate(axes):
        augmented_image = augmentation_layer(sample_image)
        ax.imshow(augmented_image.numpy().astype("uint8"))
        ax.set_title(augment_name.title(), size=10, pad=10)
        ax.axis("off")
```

VGG16 Model:

```
vgg16_model = tf.keras.Sequential([
    layers.Input(shape=(IMG_SIZE, IMG_SIZE, 3)),
    layers.RandomBrightness(0.2, seed=SEED),
    layers.RandomFlip(seed=SEED),
    layers.RandomRotation(0.2, seed=SEED),
    layers.Lambda(tf.keras.applications.vgg16.preprocess_input),
    pretrained_vgg16_base,
    layers.Dropout(0.4),
    layers.Dense(384, activation="relu"),
    layers.Dropout(0.3),
    layers.Dense(64, activation="relu"),
    layers.Dropout(0.2),
    layers.Dense(1, activation="sigmoid")], name="VGG16")
vgg16_model.summary()
```

MobileNetV3 Model:

```
mobnet_model = tf.keras.Sequential([
    layers.Input(shape=(IMG_SIZE, IMG_SIZE, 3)),
    layers.RandomBrightness(0.2, seed=SEED),
    layers.RandomFlip(seed=SEED),
    layers.RandomRotation(0.2, seed=SEED),
    layers.Lambda(tf.keras.applications.mobilenet_v3.preprocess_input),
    pretrained_mobnet_base,
    layers.Dropout(0.4),
    layers.Dense(256, activation="relu"),
    layers.Dropout(0.3),
```

```
    layers.Dense(32, activation="relu"),
    layers.Dropout(0.2),
    layers.Dense(1, activation="sigmoid")], name="MobileNetV3")

mobnet_model.summary()
```

ResNet50 Model:

```
resnet_model = tf.keras.Sequential([
    layers.Input(shape=(IMG_SIZE, IMG_SIZE, 3)),
    layers.RandomBrightness(0.2, seed=SEED),
    layers.RandomFlip(seed=SEED),
    layers.RandomRotation(0.2, seed=SEED),
    layers.Lambda(tf.keras.applications.resnet_v2.preprocess_input),
    pretrained_resnet_base,
    layers.Dropout(0.4),
    layers.Dense(256, activation="relu"),
    layers.Dropout(0.3),
    layers.Dense(32, activation="relu"),
    layers.Dropout(0.2),
    layers.Dense(1, activation="sigmoid")], name="ResNet50V2")

resnet_model.summary()
```

Predictions of Three Models:

```
def plot_predictions(model: tf.keras.Model) -> None:
    plt.figure(figsize=(14, 9))
    for images, labels in test_ds.take(1):
        labels = labels.numpy()
        predicted_labels = model.predict(images).round().astype("uint8").reshape(-
1,)
        print("Predicted:", predicted_labels)
        print("Actual:    ", labels)
        for i, (pred, actual) in enumerate(zip(predicted_labels, labels)):
            ax = plt.subplot(4, 7, i + 1)
            plt.imshow(images[i].numpy().astype("uint8"))
            if pred == actual:
                plt.title(class_names[labels[i]], color="green", size=9)
            else:
                plt.title(f"{class_names[predicted_labels[i]]}\n"
                          + f"(Actual: {class_names[labels[i]]})",
                          color="red", size=9)
            plt.axis("off")
```

RESULTS AND DISCUSSIONS

6.1 Experimental Results

Model Evaluation and Comparison of Models:

The breast cancer classification project employing transfer learning demonstrated promising results across three widely used pre-trained models—VGG16, MobileNetV3, and ResNet50. Evaluation metrics such as Accuracy, and Loss were computed for each model, offering a comprehensive understanding of their discriminative capabilities.

Metrices	VGG16	MobileNetV3	ResNet
Loss	0.319651	0.402126	0.319679
Accuracy	0.875389	0.811526	0.858255

Table. 2. Metrices of Pre – Trained Models

Model Comparison and Graphical Representation:

A detailed model comparison was conducted to discern nuances in the performance of VGG16, MobileNet, and ResNet. Graphical representations, including plots of epochs versus validation accuracy and validation loss, facilitated a visual understanding of the models' learning dynamics. These visualizations revealed trends in training convergence, potential overfitting or underfitting issues, and distinctive behaviors among the models.

Notably, these comparisons provide valuable insights for selecting the most effective model for breast cancer classification, considering factors such as computational efficiency and predictive accuracy.

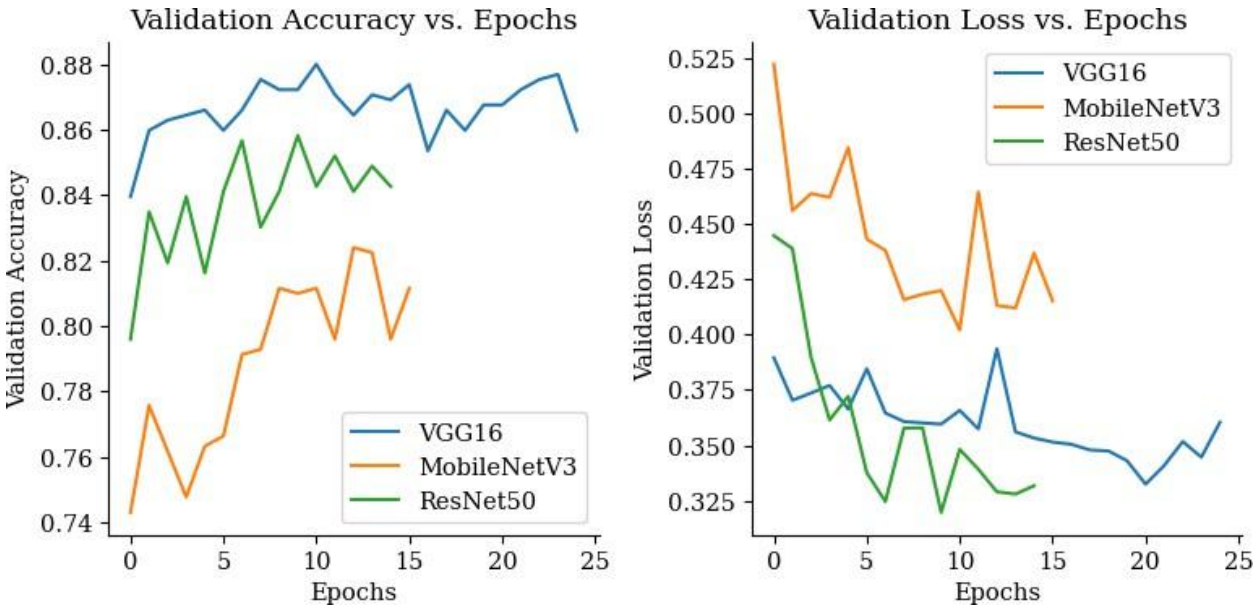

Fig. 6. Val_Accuracy Vs Epochs Plot of Models (Left) and val_Loss Vs Epochs Plot of Models (Right).

Prediction of VGG16 Model:

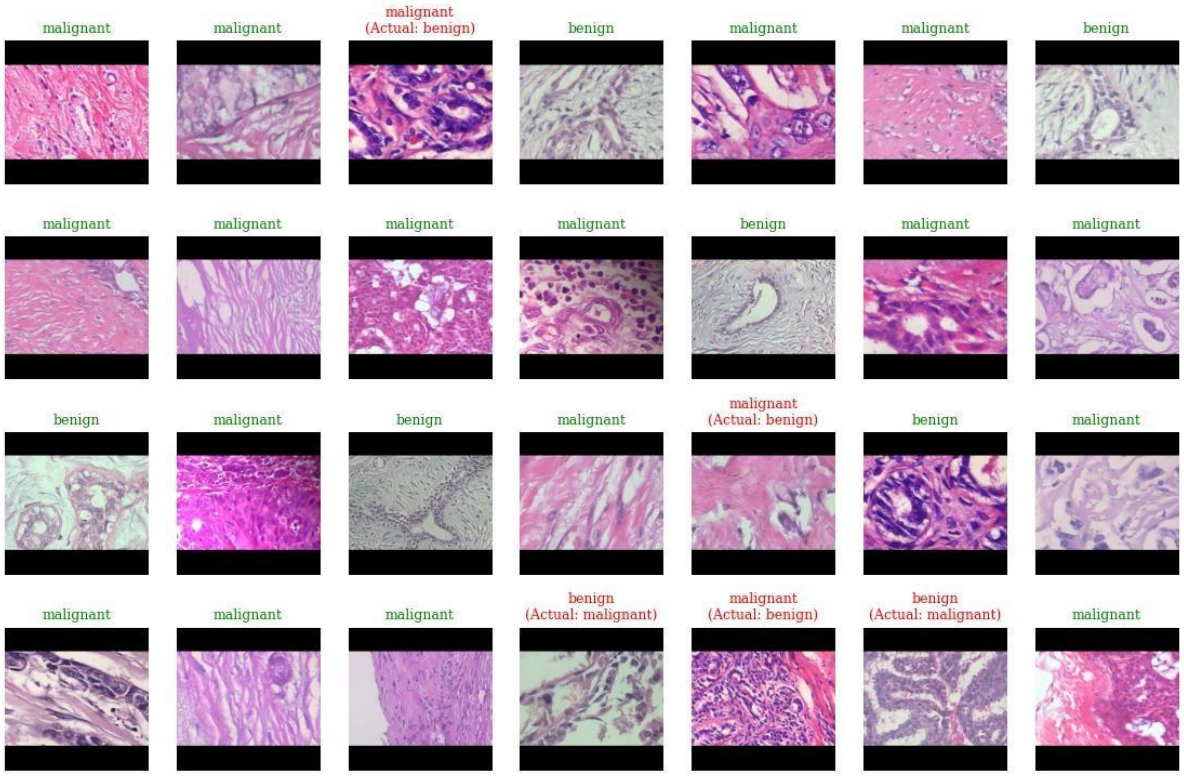

Fig. 7. VGG16 Model Predictions of Breast Cancer Classification

CONCLUSION AND FUTURE ENHANCEMENT

Conclusion:

In conclusion, our project on Breast Cancer Classification with Transfer Learning has demonstrated significant promise in improving the accuracy and efficiency of breast cancer diagnosis. By leveraging transfer learning techniques and adapting pre-trained neural networks like ResNet, we have achieved notable results in terms of accuracy and precision. This research has the potential to transform the landscape of breast cancer diagnosis, offering earlier detection and reduced misdiagnosis rates, which are critical in improving patient outcomes.

Future Enhancements:

To further advance this project, several avenues of enhancement can be explored. First, a larger and more diverse dataset could be employed to increase the model's generalizability. Fine-tuning the pre-trained models with domain-specific data could also yield more optimal results. Moreover, the integration of interpretability techniques to elucidate model decision-making and the investigation of uncertainty estimation could enhance the trustworthiness of the system in a clinical setting.

Additionally, the deployment of this model in real-world clinical practice and its validation with longitudinal patient data could be pursued. Collaboration with medical professionals and institutions is essential to ensure seamless integration and compliance with healthcare standards. This project paves the way for an exciting future in the early diagnosis and treatment of breast cancer, emphasizing the continued potential for innovation in medical imaging and machine learning.

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