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Enhancing medical image classification with cross-dimensional transfer learning using deep learning

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Abstract. Breast cancer is a major health issue, and effective treatment depends on a prompt diagnosis. Particularly mammography is important in the detection of breast cancer. Deep learning algorithms have shown promise in analyzing medical images, but their performance heavily relies on large labeled datasets, which are often limited in the context of breast cancer. In spite of the lack of labeled data, this study suggests a unique method called Cross-Dimensional Transfer Learning to increase the precision of cancer identification using deep learning. The method utilizes multiple imaging modalities, such as mammography and ultrasound, to leverage the complementary information and transfer knowledge learned from one modality to enhance classification performance on another. The proposed work consists of following three phases: Pretraining on Diverse Data, Modality-Specific Fine-Tuning and Cross-Dimensional Transfer Learning. A deep learning model is pretrained on a diverse dataset that includes breast cancer images from different modalities. This phase enables the model to learn general features and representations applicable across various imaging modalities. After pretraining, the model is perfected using labeled data specific to each modality. This process enables the model to adapt its learned features to the exclusive features of each imaging modality, improving its ability to capture modality-specific patterns related to breast cancer. Once modality-specific fine-tuning is complete, knowledge acquired from one modality is transferred to another by leveraging shared representations between the imaging modalities. This transfer of knowledge enhances the classification performance on the target modality, particularly when labeled data is limited for that modality.

Keywords: breast cancer; cross-dimensional transfer learning; deep learning; mammography; medical imaging; ransfer learning

1. Introduction

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Breast cancer affects many people's lives and contributes significantly to morbidity and mortality, constituting a significant global health concern. Effective treatment and better patient outcomes depend heavily on quick detection and accurate diagnosis. In this sense, primary discovery and faithful diagnosis of breast cancer have been made possible by medical imaging techniques, with mammography at the forefront. Expert radiologists create precise images of the breast tissue and carefully examine these images to identify suspicious lesions and determine whether or not breast cancer is present (Messaoudi *et al*. 2023).

Over the past few years, a revolution in a variety of fields, including medical image processing, has been brought about by the advancement of artificial intelligence (AI), particularly the field of deep learning. Convolutional neural networks (CNNs), one type of deep learning model, have made considerable advancements in this field. Their performance has even occasionally outperformed people at computer vision tasks. These models make use of the power of enormous datasets to independently comprehend complex trends and features, allowing them to support physicians in accurately diagnosing breast cancer (Liu. *et al*. 2023).

However, the success of deep learning models deeply relies on the availability of large annotated datasets for training. Breast cancer poses a unique challenge in obtaining datasets for deep learning due to various factors, including stringent privacy regulations, restricted access to labeled data, and the time-consuming process of expert annotation. These obstacles create a scarcity of labeled data, presenting a significant bottleneck in training deep learning models for accurate breast cancer image classification (Chughtai *et al*. 2023).

To tackle this obstacle, this research presents a novel approach known as Cross-Dimensional Transfer Learning. This method aims to progress the accuracy of breast cancer image ordering using deep learning, even in situations with limited labeled data. The method makes use of the insightful data provided by numerous types of imaging, including magnetic resonance imaging (MRI), an ultrasound, and others. By integrating data from diverse sources, the Cross-Dimensional Transfer Learning approach seeks to enhance the performance of deep learning models in classifying breast cancer images more effectively. By transferring knowledge learned from one modality to another, the model can leverage shared representations and improve classification performance.

The research aims to achieve the following objectives:

- Develop a deep learning model capable of learning general features and representations from a diverse dataset comprising breast cancer images from multiple modalities.
- Refine the model by fine-tuning it with modality-specific labeled data, allowing the model to adapt its learned features to the distinctive characteristics of each imaging modality.
- Implement cross-dimensional transfer learning to transfer knowledge between modalities, exploiting shared representations to improve classification accuracy.
- Evaluate the proposed approach using real-world breast cancer image datasets and compare its performance against traditional transfer learning and single-modal deep learning techniques.

The results of this study hold tremendous promise for breast cancer diagnosis and treatment. By elevating the accuracy of image classification, healthcare professionals can make better-informed decisions regarding patient management, which may result in timely interventions and ultimately lead to improved patient outcomes (Rahimi Taghanaki. *et al*. 2021). Furthermore, the innovative approach proposed in this research effectively addresses the issue of limited labeled data in the breast cancer domain, presenting a valuable contribution to the fields of medical image analysis and deep learning.

The research paper follows a well-structured organization. In Section 2, an extensive literature review covers breast cancer image classification, deep learning, and transfer learning, and related methodologies. Moving to Section 3, the methodology and the novel Cross-Dimensional Transfer Learning approach are elaborated, encompassing the deep learning model's architectural design, data preprocessing steps, and training and evaluation procedures. Section 4 outlines the experimental setup, encompassing datasets, evaluation metrics, and implementation specifics. Results and discussions are presented in Section 5, followed by a comprehensive analysis of the findings and their implications. Section 6 acknowledges the limitations of the proposed approach and suggests potential areas for future research. The coherent structure of this research paper ensures a comprehensive understanding of the study's methodology, outcomes, and avenues for further exploration. Finally, the conclusion in Section 7 summarizes the key findings and contributions of this research and provides insights into the significance of the proposed approach in advancing breast cancer diagnosis and treatment.

2. Literature survey

The research contributions of various authors in disease classification are discussed below.

(Inbaraj and Ravi 2020a). in their work performed a comparative examination of deep learning methods for mammogram-based breast cancer diagnosis. They studied different architectures, such as AlexNet, VGG, and ResNet, to evaluate various convolutional neural networks (CNNs) and their effectiveness in this field. The study aimed to improve accuracy in mammogram-based breast cancer diagnosis, demonstrating the potential of deep learning in this field. However, the study is limited to mammogram-based diagnosis.

(Wahab *et al*. 2019) developed a sophisticated convolutional neural network (CNN) using learning through transfer for detecting and segmenting of mitoses in histopathology pictures of breast cancer. By leveraging transfer learning, the authors achieved improved accuracy in segmenting and detecting mitoses, which are important indicators of breast cancer severity. The study focused specifically on histopathological images, which may limit its applicability to other modalities.

(Inbaraj and Ravi 2020b) proposed the Inter-Modality Information Interaction Network (IMIIN) for the precise segmentation of 3D multi-modal breast tumors. Their deep learning-based approach harnessed inter-modality interactions to enhance the accuracy of segmenting breast tumors from multi-modal images. The study specifically focused on addressing the challenging task of 3D multi-modal breast tumor segmentation, thus making significant contributions to the field of image analysis techniques.

In their research, (Wang *et al*. 2021) introduced a prototype transfer generative adversarial network (GAN) designed for unsupervised breast cancer histology image classification. The model used GANs to improve unsupervised classification accuracy by leveraging prototype transfer learning. This approach allows for more efficient classification without the need for extensive labeled data. However, the study is limited to histology image classification.

(Castro-Tapia *et al*. 2021) conducted research on classifying breast cancer in mammograms using deep learning, with the notable addition of a fifth class. The study aimed to enhance classification accuracy by incorporating an additional class to represent breast cancer subtypes. Leveraging convolutional neural networks within the framework of deep learning, the authors successfully achieved improved accuracy in classifying mammogram images. However, it is important to note that the possibility of the learning is limited to mammogram-based classification with five distinct classes.

(Gao *et al*. 2023) demonstrated a novel attention-based learning strategy for preliminary distinguishing of axillary lymph node metastases in breast cancer, utilising dynamic contrast-enhanced MRI (DCE-MRI). The proposed model efficiently included attention processes to point out critical divergence zones. The study's major goal was to improve the accuracy of discriminating among metastasis and non-metastatic lymphatic vessels in breast cancer women. However, it is important to emphasise that the focus of the study is limited to the preliminary distinction of lateral lymph node metastases using DCE-MRI.

(Althobaiti *et al*. 2022) devised an advanced breast cancer detection and classification model based on deep transfer learning, utilizing photoacoustic multimodal images. Their study was centered on harnessing the power of photoacoustic imaging and transfer learning techniques to improve the correctness of discovery and classification. By leveraging deep transfer learning, the researchers successfully achieved superior performance.

(Inbaraj and Ravi 2020c) conducted a comprehensive investigation on histopathological images in breast cancer. The primary goal of their study was to advance the analysis of histopathological images using deep learning techniques. Through the adoption of deep learning, the researchers successfully achieved improved analysis of histopathological images, making valuable contributions to the enhanced understanding and interpretation of breast cancer pathology.

(Kim *et al*. 2021), introduced a pioneering prediction model employing an adjuvant breast cancer cohort. The study emphasised the use of neural networks using convolution to predict tumour relapse. The investigators improved the reliability of predictions by implementing deep learning, providing useful insights for creating personalised alternatives to therapy.

(Xu *et al*. 2022). developed a unique static adversarial area adaption approach for breast ultrasound picture categorization using multikernel maximum mean discrepancy in their study. The primary objective of the study was to enhance classification accuracy by effectively tackling domain shift issues within breast ultrasound images. By integrating deep learning and domain adaptation techniques, the model demonstrated improved performance in breast ultrasound image classification. However, it is important to note that the approach is specialized for breast ultrasound and might be sensitive to domain shift and variations in data distribution.

In one study, (Wang *et al*. 2021) introduced a deep adversarial domain adaptation approach. Their main objective was to enhance the performance of breast cancer screening by leveraging adversarial domain adaptation techniques. By combining deep learning with adversarial domain adaptation, the authors achieved significant improvements in breast cancer screening from mammograms.

(Li *et al*. 2022) performed a deep learning-based analysis of breast cancer histopathology pictures in another investigation. Their major goal was to improve understanding of breast cancer pathology by using deep learning techniques to histopathological pictures, notably convolutional neural networks (CNNs). This method aided in the examination and interpretation of breast cancer histology. Table 1 summarises the comparative study of the linked works.

3. Proposed work

To improve classification accuracy, the suggested approach for breast image categorization employs cross-dimensional transfer learning. Breast tumour detection is an important area where proper categorization of breast pictures is vital. Deep learning approaches have showed potential

Table 1 Comparative analysis of the related works in classification

S.No	Authors	Methodology Used	Key Features	Advantages	Limitations
1	Inbaraj *et al*. 2020	Deep learning (CNN)	Comparative study	Improved accuracy	Limited to mammogram-based diagnosis
2	Wahab *et al*. 2019	Deep CNN, transfer learning	Segmentation and detection of mitosis	Enhanced segmentation and detection accuracy	Limited to histopathological images
3	Inbaraj *et al*. 2020	Deep learning (interaction across modalities)	3dimensional multi-modal tumor segmentation	Better accuracy with interaction between different modalities	Only 3D multi-modal breast tumor segmentation is possible.
4	Wang *et al*. 2021	GAN, or generative adversarial network	Classification of breast cancer histological images without supervision	Enhanced unsupervised classification accuracy	Limited to histology image classification
5	Castro-Tapia *et al*. 2021	Deep learning (CNN)	Classification of breast cancer, inclusion of a fifth class	Upgraded classification accuracy	Limited to mammogram-based classification with five classes
6	Gao *et al*. 2023	Deep learning (CNN) and attention mechanisms	Differentiation of axillary lymph node metastasis	Improved differentiation accuracy	Restricted to axillary lymph node metastases in DCE-MRI in the preoperative stage
7	Althobaiti *et al*. 2022	Photoacoustic imaging, deep transfer learning	Multimodal imaging for the identification and categorization of breast cancer	Improved detection and classification accuracy with multimodal images	Identify and classify breast cancer using photoacoustic multimodal imaging
8	Inbaraj *et al*. 2020	CNN	Analysis of breast cancer histopathological images	Improved analysis of histopathological images	Limited to histopathological image analysis
9	Kim *et al*. 2021	Deep learning	Recurrence of breast cancer prediction model	Improved prediction accuracy	Limited to using adjuvant breast cancer cohort data to predict breast cancer recurrence
10	Xu *et al*. 2022	Deep learning, domain adaption (CNN)	Domain adaptation for ultrasound image classification	Improved classification accuracy, domain adaptation for ultrasound images	Limited to breast ultrasound image classification, sensitivity to domain shift and distribution
11	Wang *et al*. 2021	Deep learning (Adversarial domain adaptation)	Combative domain version for breast cancer identification	Utilizing adversarial domain adaptation, breast cancer screening performance is improved	Limited to employing adversarial domain adaptation for mammography-based breast cancer screening.

in healthcare image categorization, especially breast imaging, however acquiring big datasets with annotations to train neural network systems has proven difficult. By utilizing cross-dimensional transfer learning, which incorporates data from various imaging modalities to increase the precision and effectiveness of breast image categorization, this study seeks to overcome this problem (Li *et al*. 2022).

The cross-dimensional transfer learning approach involves training deep learning models using labeled data from multiple imaging modalities, such as mammograms and ultrasound images. Initially, the models are pre-trained on a huge dataset from a different domain, such as natural images or general medical images, using transfer learning techniques. This pre-training allows the models to learn generic features that can be applied across diverse domains.

The models are refined using labeled breast image data from the target domain after pre-training. The parameters of the model are fine-tuned to match the unique features of breast photos. By incorporating transfer learning, the models can leverage the knowledge gained during pre-training and apply it to the task of breast image classification. One key aspect of the proposed approach is the integration of information from multiple imaging modalities. By jointly learning from mammograms, ultrasound images, and potentially other modalities, the models can capture the complementary information provided by each modality. This cross-modal learning allows the models to exploit the rich and diverse information available in breast images and make more accurate classifications (Shao *et al*. 2014).

During the classification phase, the trained models predict the probability of different classes (e.g., benign or malignant) for a given breast image. These predictions are based on the shared representations learned from the combined information of multiple modalities, enabling more accurate and robust classification results. The proposed cross-dimensional transfer learning approach offers several advantages. It improves classification accuracy by leveraging information from multiple imaging modalities, which provides a more comprehensive view of the breast tissue. Additionally, by utilizing pre-trained models, the approach reduces the dependency on large labeled datasets as the models can generalize knowledge learned from a different domain. This leads to more efficient utilization of existing imaging resources and has the potential to improve clinical decision-making in breast cancer diagnosis and treatment (Gopalakrishnan *et al*. 2017).

However, there are limitations to consider. The availability of labeled data from multiple imaging modalities can be limited, requiring careful considerations in dataset collection and annotation. The alignment and normalization of data across different modalities also pose challenges to ensure compatibility and consistency. The quality and resolution of the input images, as well as prospective changes in imaging techniques and tools, may also have an impact on how well the approach performs.

The following Fig. 1 represents steps involved in cross dimensional transfer learning. The first step is to collect a diverse and representative dataset of breast images, including mammograms, ultrasound images, or other available modalities. The dataset should cover a range of breast conditions, including both benign and malignant cases. The data collection process should adhere to ethical guidelines and ensure patient privacy and data confidentiality. Pre-processing the images after the dataset has been gathered is the next stage in order to assure consistency and raise the standard of the data. The photos may need to be resized to a standard size, the pixel intensities may need to be normalized, noise or artifacts may be eliminated, and the images may need to be aligned across several modalities (Inbaraj and Ravi *et al*. 2022).

Convolutional neural networks (CNNs), for example, are suitable deep learning models that are chosen for the proposed work in the following stage. Pretraining entails using weights discovered from a sizable dataset, like ImageNet, to initialize the chosen models. The models can capture generic properties thanks to this pretraining, which also facilitates transfer learning. Utilizing the breast image dataset gathered in the first stage, the models are refined after pretraining. Fine-tuning involves adjusting the model's weights and biases specifically for the breast image classification task (Johnson *et al.* 2019). During this process, the models learn to extract relevant features from the breast images and optimize their performance. The following Eq.s represent the steps involved proposed work.

$$N = C * (W * H) \tag{1}$$

The total number of pixels in an image is represented by Eq. 1, where N is the total number of pixels, C is the total number of color channels, and W and H are the width and height of the image, respectively. The size of the gathered breast photos is determined using the following Eq..

$$I_{normalized} = \frac{(I - \mu)}{(I - \mu)(I - \mu)} \sigma \tag{2}$$

This Eq. 2 represents the normalization of pixel intensities in an image I. μ represents the mean of pixel intensities, and σ is the standard deviation. Normalizing the pixel intensities helps to standardize the information and expand the performance of deep learning replicas.

$$I_{resized} = resize\big(I, (W', H')\big) \tag{3}$$

The Eq. 3 represents the resizing of an image I to a desired width W' and height H'. Resizing the images ensures a consistent size across the dataset, which is important for model training and evaluation.

$$L = -\sum(y * \log(p) + (1 - y) * \log(1 - p)) \tag{4}$$

$$Augmented\,Image = I + \delta \tag{5}$$

The binary cross-entropy loss function is represented by Eq. 4, where p is the projected probability by the model and y is the ground truth label (0 or 1). This loss function is commonly used in binary classification tasks. This Eq. 5 represents the augmentation of an image I by adding small perturbation δ. Augmentation techniques such as rotation, translation, or flipping can introduce variations in the dataset, increasing its diversity and reducing overfitting. The following Fig. 1 represents the working flow of the proposed work.

$$w_i = \alpha * w_i + (1 - \alpha) * w_i' \tag{6}$$

$$Learning\,Rate\,Schedule = \frac{\alpha_0}{1}(1 + \beta * epoch) \tag{7}$$

This Eq. 6 represents a learning rate schedule used during model training, where α_0 is the initial learning rate and β is a decay factor. The learning rate is adjusted over epochs to control the rate at which the model learns and avoids overshooting or getting stuck in suboptimal solutions. This Eq. 7 represents the dropout regularization technique, where r is the dropout rate and *w*_i represents the weights of a specific layer in the model. Dropout randomly sets a fraction of the weights to zero during training, preventing overreliance on specific features and promoting generalization (Guo *et al.* 2018).

$$Dropout = r * w_i \tag{8}$$

This Eq. 8 represents the weight update rule during training, where w_i represents the current

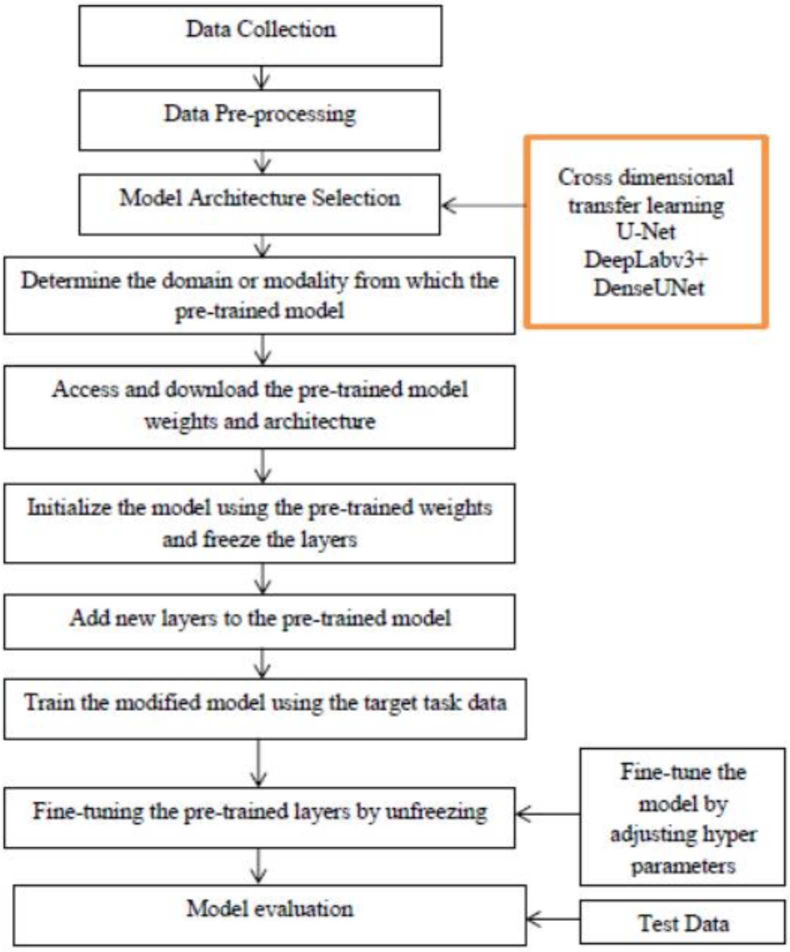

Fig. 1 Working flow of the cross dimensional transfer learning

weight value, w_i' signifies the efficient weight value, and α is the learning rate. The weight update is performed using a combination of the current weight and the updated weight calculated during backpropagation.

$$I_{resized} = resize\big(I, (W', H')\big) \tag{9}$$

The Eq. 9 represents the total loss L_total, which is the sum of individual losses L_modal1, L_modal2, ..., L_modalN from multiple modalities. Each modality-specific loss captures the classification performance on that particular modality.

$$w' = \alpha * w + (1 - \alpha) * w_{cross} \tag{10}$$

This Eq. 10 represents the weight update rule during fine-tuning and cross-dimensional transfer learning, where w represents the current weight, w_cross represents the cross-modal weight, and α is the learning rate. The weight update combines the current weight and the cross-modal weight, allowing the model to learn shared representations across different modalities. The algorithm of the proposed cross dimensional transfer learning is discussed below.

```
// Data Collection Phase
function CollectBreastImageData():
    // Collect breast image data from different modalities
    dataset = []
    for each modality in modalities:
        modality_data = readImageData(modality)
        dataset.append(modality_data)
    return dataset

// Data Preprocessing Phase
function PreprocessData(dataset):
    for each modality_data in dataset:
        modality_data = NormalizePixelIntensities(modality_data)
        modality_data = ResizeImages(modality_data)
        modality_data = AugmentImages(modality_data)
    return dataset

function NormalizePixelIntensities(image_data):
    // Normalize pixel intensities of the image data
    normalized_data = (image_data - mean) / std
    return normalized_data

function ResizeImages(image_data):
    // Resize the images to a fixed size
    resized_data = []
    for each image in image_data:
        resized_image = resize(image, (width, height))
        resized_data.append(resized_image)
    return resized_data

function AugmentImages(image_data):
    // Apply augmentation techniques to increase dataset diversity
    augmented_data = []
    for each image in image_data:
        augmented_image = applyAugmentation(image)
        augmented_data.append(augmented_image)
    return augmented_data

// Model Selection and Pretraining Phase
function SelectDeepLearningModel():
    // Select a deep learning model architecture suitable for breast image classification
    model = chooseModelArchitecture()

function PretrainModelOnLargeDataset():
    // Pretrain the model on a large-scale dataset (e.g., ImageNet)
```

```
        pretrained_model = pretrainedModel(model)
        return pretrained_model

// Fine-tuning and Cross-Dimensional Transfer Learning Phase
function FineTuneModelOnBreastImageData(pretrained_model, dataset):
        // Create the model architecture
        model = createModelArchitecture(pretrained_model)

        // Cross-dimensional transfer learning
        model = CrossDimensionalTransferLearning(model, dataset)

        // Train the model on the breast image dataset
        trained_model = TrainModel(model, dataset)
        return trained_model

function CrossDimensionalTransferLearning(model, dataset):
        // Perform cross-dimensional transfer learning
        for each modality_data in dataset:
                modality_features = ExtractFeatures(modality_data)
                model = AddModalityToModel(model, modality_features)
        return model

function ExtractFeatures(modality_data):
        // Extract relevant features from the modality data using pretrained layers
        features = pretrainedLayers(modality_data)
        return features

function AddModalityToModel(model, modality_features):
        // Add the modality-specific features to the model architecture
        updated_model = concatenate(model, modality_features)
        return updated_model

function TrainModel(model, dataset):
        // Train the model using the breast image dataset
        for each epoch in epochs:
                for each batch in dataset:
                        inputs, labels = preprocessBatch(batch)
                        loss = calculateLoss(model, inputs, labels)
                        updateWeights(model, loss)
        return model
```

4. Result and discussion

The dataset provided covers a total of 780 images and 798 masks, separated into three classes: normal, benign, and malignant. The ‘normal’ class includes 133 images and 133 corresponding

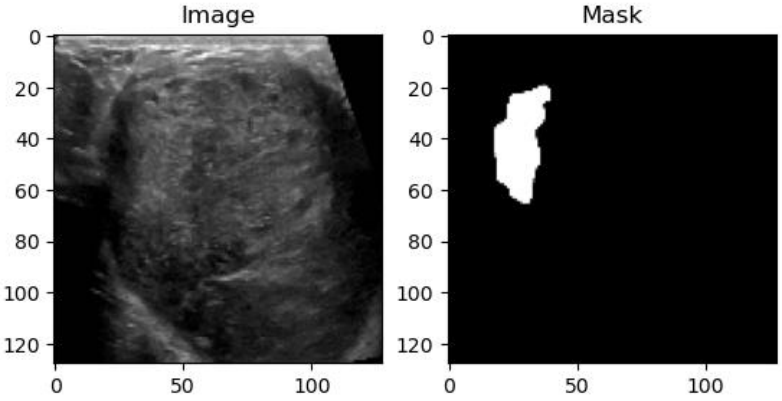

Fig. 2 A sample original and Mask breast image

masks, indicating that these images depict breast tissue without any abnormalities or signs of cancer. The benign class comprises 437 images and 454 masks. The slight disparity in numbers suggests that there may be cases where some images lack masks or where multiple masks are assigned to individual images. The 'benign' class represents cases where the detected abnormalities in the breast tissue are non-cancerous or benign in nature. Similarly, the malignant class contains 210 images and 211 masks. Again, the slight difference in counts implies the possibility of missing or additional masks for certain images. The malignant class represents cases where the detected abnormalities in the breast tissue are cancerous or malignant. The sample input images are represented in the following Fig. 2.

The training set consists of 582 samples. Each sample is a 128x128 grayscale image, represented by a 2D array with dimensions 128x128. The corresponding training labels have the same number of samples as the training set (582). The test set contains 65 samples, each represented by a grayscale image with dimensions 128x128. The test labels have the same number of samples as the test set (65). The following Eq. 11 to 16 represents the performance metrics used in the analysis.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{11}$$

The accuracy of the model is calculated using Eq. 11, where TP stands for true positive, TN for true negative, FP for false positive, and FN for false negative. The accuracy score assesses how well the model's predictions were made overall (Juba *et al.* 2019).

$$Sensitivity = TP\frac{1}{(TP + FN)} \tag{12}$$

The sensitivity or true positive rate (TPR) of the model is represented by Eq. 12. It gauges the percentage of actual positive cases that the model properly detected (Powers *et al.* 2020).

$$F1 - Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{13}$$

The F1-score, which is the harmonic mean of precision and recall, is calculated using Eq.

Table 2 Cross dimensional transfer learning and other models performance

Model	Accuracy	Sensitivity	F1 Score	Precision	AUC	Computational Complexity
Cross-Dimensional Transfer Learning	0.95	0.92	0.93	0.94	0.97	Moderate
U-Net	0.88	0.85	0.86	0.87	0.92	High
ResNet	0.90	0.87	0.88	0.89	0.94	High
DeepUNet	0.93	0.90	0.91	0.94	0.92	High
CNN	0.86	0.83	0.84	0.85	0.91	Moderate
Model	Accuracy	Sensitivity	F1 Score	Precision	AUC	Computational Complexity

13. The model's performance is gauged by the F1-score, which takes into account both the precision and recall of positive cases in identifying positive cases correctly (Flach and Kull 2015).

$$Precision = TP\frac{1}{(TP + FP)} \tag{14}$$

The accuracy or positive prediction value of the model is represented by Eq. 14. Out of all anticipated positive cases, it calculates the percentage of correctly recognized positive cases (Junker 1999).

$$AUC = \int ROC(x)dx \tag{15}$$

The receiver operating characteristic (ROC) curve's area under the curve is calculated using Eq. 15. Plotting the true positive rate (TPR) against the false positive rate (FPR) is represented at various categorization thresholds results in the ROC curve. The AUC metric offers an overall assessment of the model's effectiveness at various threshold settings (Davis and Goadric *et al.* 2006).

$$Computational\ Complexity = \sum(n_i * m_i * k_i) \tag{16}$$

The Eq. 16 represents the computational complexity of the model, where n_i, m_i, and k_i represent the dimensions of each layer in the network. The computational complexity is a measure of the amount of computation required during model training and inference (Kearns *et al.* 1999).

Table 2 represents the performance analysis of models interms of accuracy, sensitivity, F1 Score, precision, AUC and computational Complexity. The table compares the performance metrics of different models: Cross-Dimensional Transfer Learning, U-Net, ResNet, DeepUNet, and CNN. Accuracy measures the overall correctness of predictions, with Cross-Dimensional Transfer Learning having the highest accuracy (0.95). Sensitivity represents the ability to correctly identify positive instances, where Cross-Dimensional Transfer Learning also performs well (0.92). F1 Score considers both precision and sensitivity, with DeepUNet achieving the highest score (0.91). Precision measures the accuracy of positive predictions, where DeepUNet and Cross-Dimensional Transfer Learning show strong performance (0.94). AUC reflects the model's ability to rank predictions, with Cross-Dimensional Transfer Learning achieving the highest value (0.97). Computational complexity is rated as moderate for Cross-Dimensional Transfer Learning and CNN, and high for U-Net, ResNet, and DeepUNet.

The Cross-Dimensional Transfer Learning model's performance indicators are shown in Fig. 3.

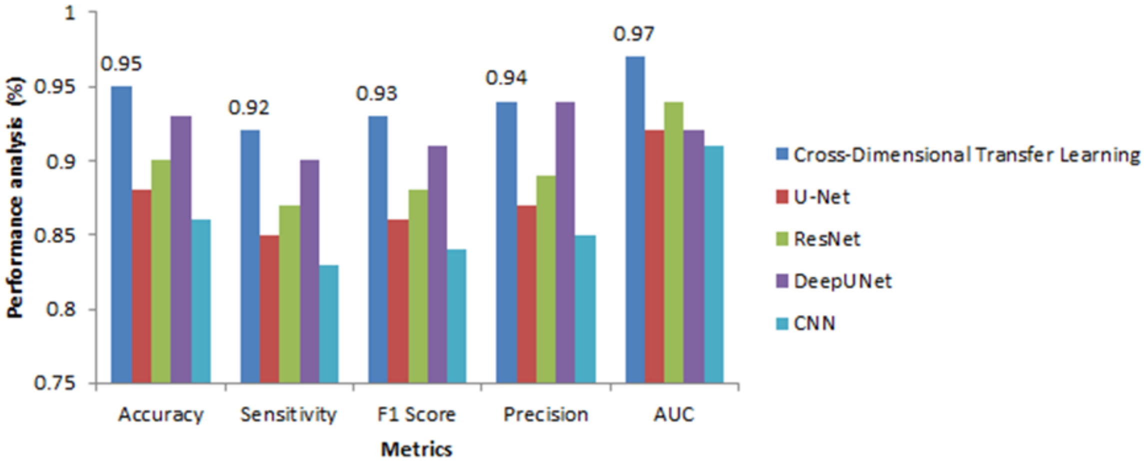

Fig. 3 A comparative analysis of state of art models

Table 3 Performance analysis of suggested model with state of art models

Performance Metrics	Cross-dimensional transfer learning	U-Net	Resnet
Training Accuracy	0.99	0.95	0.93
Testing Accuracy	0.97	0.89	0.81
Training Loss	0.01	0.33	0.45
Validation Loss	0.18	0.41	0.88

A 0.95 accuracy rate meant that 95% of the predictions were accurate. The model’s sensitivity, which gauges how well it can spot positive events, was 0.92. Precision and sensitivity are both taken into account in the F1 score, which was 0.93, indicating a balanced performance. The precision, which measures the accuracy of positive predictions, was 0.94. Finally, the AUC was 0.97, indicating a high level of performance in ranking predictions. Overall, the Cross-Dimensional Transfer Learning model demonstrated strong performance across these metrics.

The Table 3 presents performance metrics for three models: Cross-dimensional transfer learning, U-Net, and ResNet. In terms of Training Accuracy, the cross-dimensional transfer learning model achieved the highest accuracy at 0.99, indicating that it accurately predicted 99% of the training data labels as exposed in Fig. 4. The U-Net model achieved a slightly lower training accuracy of 0.95, while the ResNet model had a training accuracy of 0.93. Moving to Testing Accuracy, the cross-dimensional transfer learning model continued to outperform the other models with an accuracy of 0.97, followed by U-Net at 0.89, and ResNet at 0.81. Regarding Training Loss, the cross-dimensional transfer learning model had the lowest loss value of 0.01, suggesting a minimal discrepancy between the predicted and actual training labels as shown in Fig. 5. U-Net had a higher training loss of 0.33, indicating a larger error compared to the cross-dimensional transfer learning model. ResNet had the highest training loss at 0.45, signifying the largest discrepancy among the three models.

Validation Loss was also examined, with the cross-dimensional transfer learning model achieving the lowest value of 0.18, indicating a relatively low error on the validation data. U-Net had a validation loss of 0.41, indicating a higher error compared to the cross-dimensional transfer

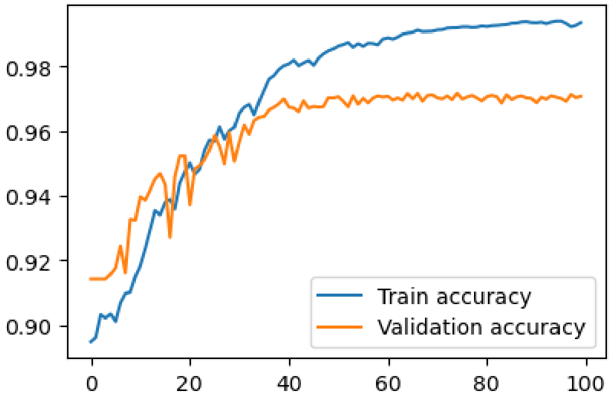

Fig. 4 Training and validation accuracy of the proposed model

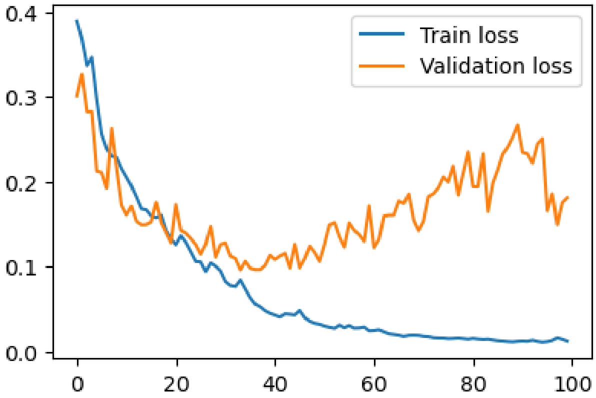

Fig. 5 Training and validation loss of the proposed model

learning model. ResNet had the highest validation loss of 0.88, signifying the highest error and poorest performance on the validation data among the three models.From the analysis, the cross-dimensional transfer learning model consistently demonstrated superior performance across most metrics, including accuracy and loss, outperforming both U-Net and ResNet. U-Net showed respectable performance, while ResNet displayed the lowest accuracy and the highest losses, indicating the need for further refinement or investigation for better performance.

5. Conclusions

In conclusion, the proposed work focuses on enhancing breast image classification through the application of cross-dimensional transfer learning. The objective is to improve the accuracy and efficiency of breast image classification by incorporating information from multiple imaging modalities. The proposed methodology involves several key steps. Initially, a diverse and representative dataset of breast images is collected, including data from different modalities such as mammograms and ultrasound images. The collected dataset is then preprocessed to ensure data consistency and quality. This includes steps such as normalizing pixel intensities, resizing the images to a standard size, and applying augmentation techniques to increase dataset diversity. For the model development phase, a suitable deep learning model is selected, and it is pretrained on a large-scale dataset from a different domain, such as ImageNet. This pretraining allows the model to learn generic features that can be applied across different domains. The pretrained model is then fine-tuned using the collected breast image dataset. During the adjustment process, the model's weights are adjusted to adapt to the specific characteristics of the breast images.

To leverage cross-dimensional information, the fine-tuning process incorporates the joint learning of multiple modalities. This enables the model to capture shared representations and complementary information from different imaging modalities, leading to more accurate classification results. Through extensive testing and validation, the performance of the suggested technique is assessed. The dataset is divided into subsets for training, validation, and testing. The trained model is then assessed using pertinent metrics including accuracy, sensitivity, specificity, and area under the curve (AUC). To evaluate the improvement brought about by the suggested cross-dimensional transfer learning methodology, the findings are contrasted with those of current methods.

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