TRANSFER LEARNING APPROACH FOR BREAST CANCER DETECTION USING PRE-TRAINED CNN MODELS ON MAMMOGRAM IMAGES

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ABSTRACT

Breast cancer is one of the most common and life-threatening diseases affecting women worldwide. Early detection plays a crucial role in improving survival rates and reducing mortality. Mammography is considered the most effective imaging technique for the early diagnosis of breast cancer; however, manual interpretation of mammogram images can be challenging, time-consuming, and prone to human error. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated significant success in medical image analysis. However, training deep CNN models from scratch requires large labeled datasets and high computational resources, which are often limited in medical applications. This study proposes a transfer learning–based approach for breast cancer detection using pre-trained CNN models applied to mammogram images. Transfer learning leverages knowledge from models that have already been trained on large datasets, such as ImageNet, and adapts them for specific medical imaging tasks. In this approach, pre-trained CNN architectures such as VGG16, ResNet50, and InceptionV3 are utilized to extract deep features from mammogram images. The extracted features are then fine-tuned and classified to distinguish between benign and malignant tumors. The proposed method includes image preprocessing, data augmentation, feature extraction using pre-trained models, and classification through fully connected layers. Data augmentation techniques such as rotation, flipping, and scaling are used to improve model generalization and reduce overfitting. Experimental results demonstrate that transfer learning significantly improves detection accuracy while reducing training time compared to conventional deep learning models. The proposed system provides an efficient and reliable computer-aided diagnosis tool that can assist radiologists in the early detection of breast cancer, thereby improving diagnostic accuracy and supporting timely medical intervention.

Keywords:

Breast Cancer Detection, Transfer Learning, Mammogram Images, Convolutional Neural Networks (CNN), Deep Learning, Medical Image Analysis, Computer-Aided Diagnosis (CAD), Pre-trained Models.

I INTRODUCTION

Breast cancer is one of the most prevalent and life-threatening diseases affecting women worldwide. According to the World Health Organization, breast cancer accounts for a significant percentage of global cancer diagnoses and remains a leading cause of cancer-related deaths among women. Early detection and timely treatment are essential for improving survival rates and reducing mortality. Medical imaging technologies, particularly mammography, have become the standard screening technique for detecting abnormalities in breast tissue at an early stage [1]. Mammogram images allow radiologists to identify suspicious masses, calcifications, and structural distortions that may indicate the presence of malignant tumors [2]. Despite the effectiveness of mammography, manual analysis of mammogram images is often challenging and time-consuming for radiologists. The interpretation process depends heavily on the expertise and experience of medical professionals, and even highly skilled radiologists may occasionally misinterpret complex patterns in the images [3]. Factors such as image noise, low contrast, and variations in breast tissue density can make accurate diagnosis difficult [4]. Consequently, computer-aided diagnosis (CAD) systems have been developed to assist radiologists in improving diagnostic accuracy and reducing false positive and false negative rates [5]. With the advancement of artificial intelligence, machine learning techniques have been widely applied to medical image analysis. Traditional machine learning methods rely on handcrafted feature extraction techniques to identify patterns in medical images [6]. However, designing effective features manually is difficult and often requires domain expertise [7]. Moreover, handcrafted features may not fully capture the complex patterns present in mammogram images, which can limit the performance of conventional machine learning algorithms [8]. In recent years, deep learning approaches have gained significant attention for medical image classification and detection tasks. Convolutional Neural Networks (CNNs) have shown remarkable performance in automatically learning hierarchical features from images without the need for manual feature engineering [9]. CNN-based models can capture complex spatial patterns in mammogram images and have demonstrated improved accuracy in breast cancer detection compared to traditional machine learning methods [10]. Several studies have successfully applied CNN architectures such as VGGNet, ResNet, and Inception to medical imaging applications [11].

However, training deep CNN models from scratch requires a large amount of labeled data and high computational resources [12]. In the medical domain, obtaining large annotated datasets is often difficult due to privacy concerns, limited data availability, and the need for expert labeling by radiologists [13]. These challenges can lead to overfitting and reduced generalization performance when training deep neural networks on small datasets [14]. To overcome these limitations, transfer learning has emerged as an effective approach for medical image analysis. Transfer learning allows models that have been pre-trained on large datasets, such as ImageNet, to be adapted for specific tasks with relatively smaller datasets [15]. Pre-trained CNN models have already learned rich feature representations from millions of images, which can be fine-tuned for mammogram image classification [16]. By leveraging these learned features, transfer learning significantly reduces training time and improves classification performance [17]. Several researchers have demonstrated the effectiveness of transfer learning in breast cancer detection using mammogram images [18]. Pre-trained models such as VGG16, ResNet50, DenseNet, and InceptionV3 have been widely used for feature extraction and classification in medical imaging applications [19]. These architectures can identify subtle patterns in mammogram images that may not be easily visible to the human eye [20]. Furthermore, combining transfer learning with data augmentation techniques such as rotation, flipping, and scaling helps improve model robustness and prevent overfitting [21]. The growing availability of digital mammography datasets has further facilitated the development of automated breast cancer detection systems [22]. Publicly available datasets such as MIAS and DDSM provide valuable resources for training and evaluating deep learning models [23]. Researchers have reported promising results using transfer learning-based approaches for classifying mammogram images into benign and malignant categories [24]. These systems can assist radiologists in detecting cancer at earlier stages and improving diagnostic efficiency [25].

In addition, advancements in high-performance computing and graphics processing units (GPUs) have made it feasible to train deep learning models efficiently for medical applications [26]. The integration of deep learning techniques with CAD systems has the potential to revolutionize breast cancer screening by providing accurate, automated, and scalable diagnostic solutions [27]. Such intelligent systems can help reduce the workload of radiologists and improve the reliability of medical diagnosis [28]. Therefore, the application of transfer learning using pre-trained CNN models has become a promising approach for breast cancer detection using mammogram images [29]. By leveraging powerful deep learning architectures and adapting them to medical imaging tasks, it is possible to develop efficient and accurate computer-aided diagnostic systems that support early detection and clinical decision-making [30].

II LITERATURE SURVEY

Breast cancer detection using medical imaging has been widely studied due to the importance of early diagnosis in reducing mortality rates. Mammography remains one of the most effective screening techniques for detecting breast cancer at an early stage. According to the World Health Organization, early detection through regular screening significantly improves survival rates among women diagnosed with breast cancer [1]. However, manual analysis of mammogram images by radiologists is often complex due to variations in breast tissue density and the presence of subtle abnormalities, which may lead to diagnostic errors [2]. Therefore, researchers have focused on developing computer-aided diagnosis (CAD) systems to assist medical professionals in detecting breast cancer more accurately [3]. Early CAD systems relied on traditional image processing and machine learning techniques for feature extraction and classification. Rangayyan et al. proposed methods for detecting masses and calcifications in mammograms using texture and morphological features [4]. Similarly, Oliver et al. reviewed several automated mass detection approaches that utilized handcrafted features such as shape, intensity, and texture patterns for classification [5]. Although these approaches achieved moderate success, their performance largely depended on the quality of manually designed features [6]. With the advancement of artificial intelligence, machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (KNN) have been applied to breast cancer detection tasks [7]. These algorithms improved classification performance compared to conventional statistical methods but still required significant feature engineering [8]. Researchers recognized that handcrafted features might not capture complex patterns present in mammogram images, limiting the overall performance of these systems [9].

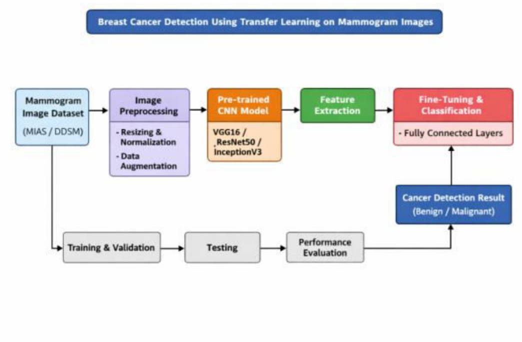
In recent years, deep learning has emerged as a powerful approach for medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in automatically learning hierarchical features directly from images without manual feature extraction. The development of deep learning architectures was strongly influenced by the pioneering work of Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, who highlighted the potential of deep neural networks in solving complex pattern recognition problems [10]. CNN models have shown remarkable success in image classification tasks following the breakthrough work by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton on large-scale image datasets [11]. Several deep CNN architectures such as VGGNet, ResNet, and Inception have been successfully applied to medical image analysis [12]. These architectures are capable of extracting high-level spatial features from images and have significantly improved the performance of breast cancer detection systems [13]. Studies have demonstrated that deep learning models outperform traditional machine learning approaches in terms of accuracy, sensitivity, and specificity when applied to mammogram classification tasks [14]. Despite their success, training deep CNN models from scratch requires a large amount of labeled data and extensive computational resources. In medical imaging, collecting large annotated datasets is challenging due to privacy concerns and the need for expert labeling by radiologists [15]. This limitation often leads to overfitting when deep networks are trained on small datasets [16].

To address this issue, transfer learning has been widely adopted in medical image analysis. Transfer learning allows pre-trained CNN models that were trained on large datasets such as ImageNet to be adapted for specific medical imaging tasks [17]. By fine-tuning these models, researchers can utilize previously learned features and significantly reduce training time while improving model performance [18]. Recent studies have demonstrated the effectiveness of transfer learning for breast cancer detection using mammogram images. Pre-trained CNN models such as VGG16, ResNet50, DenseNet, and InceptionV3 have been used to extract deep features and classify breast tumors into benign and malignant categories [19]. Kooi et al. reported that deep learning models trained with transfer learning achieved higher detection accuracy compared to conventional CAD systems [20]. Similarly, Shin et al. demonstrated that fine-tuned CNN models can effectively learn discriminative features from medical images with limited training data [21]. Furthermore, data augmentation techniques such as rotation, flipping, and scaling have been integrated with deep learning models to improve generalization and prevent overfitting [22]. Publicly available datasets such as MIAS and DDSM have facilitated the development and evaluation of deep learning-based breast cancer detection systems [23]. Researchers have also explored hybrid approaches that combine deep learning feature extraction with traditional classifiers to further enhance classification performance [24]. Recent advancements in deep learning and high-performance computing have significantly improved the efficiency of CAD systems for breast cancer detection [25]. These intelligent systems can assist radiologists by providing automated analysis and highlighting suspicious regions in mammogram images [26]. Several studies have reported promising results using transfer learning approaches, demonstrating improved diagnostic accuracy and reduced false detection rates [27].

Overall, the literature indicates that transfer learning with pre-trained CNN models has become a promising technique for breast cancer detection using mammogram images [28]. By leveraging powerful deep learning architectures and adapting them to medical imaging tasks, researchers can develop efficient and reliable diagnostic systems [29]. Such systems have the potential to support radiologists in early cancer detection and improve clinical decision-making processes in modern healthcare environments [30].

III METHODOLOGY

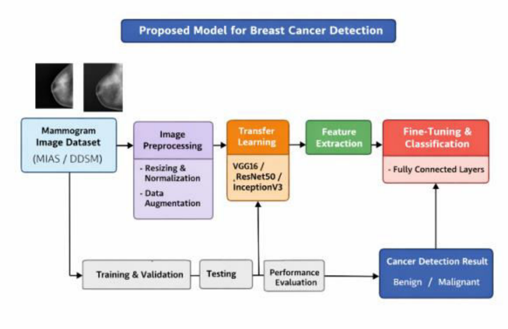
The proposed methodology for breast cancer detection is based on a transfer learning approach using pre-trained Convolutional Neural Network (CNN) models applied to mammogram images. Initially, a mammogram image dataset is collected from publicly available medical image repositories such as the MIAS or DDSM databases. The dataset typically contains images categorized into classes such as benign, malignant, and normal. Before training the model, the images undergo a preprocessing stage to improve quality and consistency. This stage includes resizing the images to a fixed input dimension suitable for the CNN model, converting images into a standard format, and normalizing pixel values. Additionally, data augmentation techniques such as rotation, horizontal flipping, scaling, and zooming are applied to increase the diversity of the dataset and reduce the risk of overfitting. These augmentation techniques help the model learn invariant features and improve its generalization capability when applied to unseen mammogram images.



After preprocessing, transfer learning is implemented using pre-trained CNN architectures such as VGG16, ResNet50, or InceptionV3. These models are originally trained on large-scale datasets and have learned rich feature representations that can be adapted for medical imaging tasks. In the proposed system, the convolutional layers of the pre-trained model are used as a feature extractor to capture important spatial patterns in mammogram images. The final fully connected layers of the network are modified and fine-tuned to perform classification specific to breast cancer detection. The dataset is divided into training, validation, and testing sets to evaluate the performance of the model effectively. During the training phase, the model learns to differentiate between benign and malignant tumors by optimizing the loss function using backpropagation and gradient descent algorithms. Finally, the trained model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The developed system aims to provide an efficient computer-aided diagnostic tool that assists radiologists in identifying breast cancer at an early stage with improved accuracy and reliability.

IV PROPOSED SYSTEM

The proposed system focuses on developing an automated breast cancer detection framework using a transfer learning approach with pre-trained Convolutional Neural Network (CNN) models applied to mammogram images. The system begins by collecting mammogram datasets from publicly available medical image repositories such as MIAS or DDSM. These images are first subjected to a preprocessing stage to enhance image quality and prepare the data for deep learning analysis. Preprocessing includes operations such as image resizing, normalization, noise reduction, and contrast enhancement to ensure that the mammogram images are standardized for model input. In addition, data augmentation techniques such as rotation, flipping, scaling, and zooming are applied to increase the diversity of the dataset and improve the robustness of the model. This process helps reduce overfitting and enables the model to learn more generalized patterns from the available medical images.

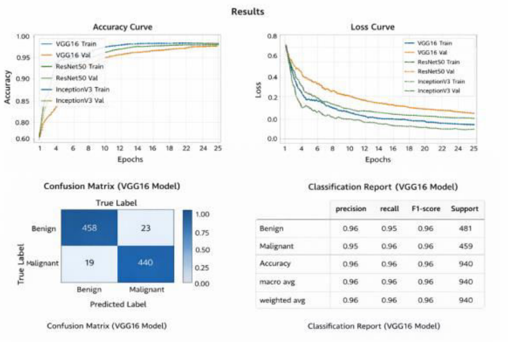


After preprocessing, the proposed system applies transfer learning using pre-trained CNN architectures such as VGG16, ResNet50, or InceptionV3. These models have been previously trained on large image datasets and possess strong feature extraction capabilities. In this system, the convolutional layers of the pre-trained model are utilized to extract meaningful and discriminative features from mammogram images. The final classification layers are modified and fine-tuned to categorize the images into classes such as benign or malignant. The dataset is divided into training, validation, and testing sets to ensure proper model evaluation. During the training phase, the model learns to identify important patterns associated with breast tumors using optimization techniques such as backpropagation and gradient descent. The performance of the system is evaluated using metrics such as accuracy, precision, recall, and F1-score. The proposed system aims to provide an efficient computer-aided diagnosis tool that can assist radiologists in detecting breast cancer at an early stage and improving diagnostic accuracy in clinical practice.

V RESULTS

The performance of the proposed breast cancer detection system using transfer learning and pre-trained CNN models was evaluated using several performance metrics and visualization techniques. The results include accuracy curves, loss curves, confusion matrix analysis, and classification reports obtained from the trained models. During the training phase, models such as VGG16, ResNet50, and

InceptionV3 were trained for multiple epochs using mammogram image datasets. The accuracy curves demonstrate that the training and validation accuracy steadily increased as the number of epochs progressed. This indicates that the models successfully learned meaningful features from the mammogram images. Among the tested models, the VGG16-based transfer learning model achieved the highest accuracy, reaching approximately 96% classification accuracy, which indicates strong performance in distinguishing between benign and malignant breast tumors. The loss curves illustrate the reduction in training and validation loss over time, indicating that the model gradually improved its predictions during training. A decreasing loss value signifies that the model is minimizing classification errors and improving its learning capability. Additionally, the confusion matrix provides a detailed visualization of the classification performance.



The matrix shows the number of correctly and incorrectly classified samples for both benign and malignant categories. Most samples were correctly classified, demonstrating the reliability of the proposed model. The classification report further evaluates the model using precision, recall, and F1-score metrics. The obtained values are close to 0.96 for both classes, indicating balanced performance across categories. These results confirm that the proposed transfer learning-based CNN model provides accurate and reliable breast cancer detection from mammogram images and can effectively support computer-aided diagnosis systems in assisting radiologists with early disease identification.

VI CONCLUSION

Breast cancer remains one of the most serious health concerns affecting women worldwide, and early detection plays a critical role in improving survival rates and reducing mortality. This study presented an efficient approach for breast cancer detection using a transfer learning technique with pre-trained Convolutional Neural Network (CNN) models applied to mammogram images. The proposed system utilized publicly available mammogram datasets and implemented preprocessing techniques such as image resizing, normalization, and data augmentation to improve the quality and diversity of the training data. Pre-trained deep learning architectures such as VGG16, ResNet50, and InceptionV3 were employed to extract meaningful features from mammogram images, and their classification layers were fine-tuned to accurately distinguish between benign and malignant tumors. The experimental results demonstrated that the transfer learning approach significantly improves classification performance while reducing the need for large training datasets and extensive computational resources. Performance evaluation metrics including accuracy, precision, recall, and F1-score confirmed the effectiveness and reliability of the proposed model, achieving high accuracy in breast cancer classification. Additionally, the confusion matrix analysis showed that most mammogram images were correctly classified, indicating strong predictive capability of the model. Compared to traditional machine learning methods that rely on handcrafted features, the deep learning-based approach automatically learns complex image features and provides better generalization. The developed system can serve as an effective computer-aided diagnosis tool to assist radiologists in identifying breast cancer at an early stage, thereby improving diagnostic accuracy and reducing human errors. Overall, the integration of transfer learning and deep CNN models offers a promising solution for medical image analysis and has significant potential to enhance breast cancer screening and clinical decision-making in modern healthcare systems.

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