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Breast Cancer Classification Using ResNet-50 Technique and Wavelet-Based Preprocessing

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ABSTRACT

Breast cancer is a prevalent and complex disease that necessitates accurate classification for timely diagnosis and effective treatment. This paper proposes a breast cancer classification system that leverages the ResNet-50 model and incorporates transfer learning. The system utilizes two separate ResNet-50 models: one for normal and abnormal classification and another for benign and malignant classification within the abnormal category. The experimental evaluation employs three datasets: MIAS, DDSM, and CBIS-DDSM. The wavelet transform technique is applied as a pre-processing step to enhance mammography images. The system achieves outstanding performance with high accuracies of 99.48% and 99.25% for the first and second models, respectively. Additionally, sensitivity and specificity values of up to 99.32% and 99.17% for the first model and 99.07% and 98.89% for the second model are obtained. Notably, the DDSM dataset consistently outperforms other datasets in both models. The proposed system demonstrates the efficacy of the ResNet-50 model and the wavelet transform technique in breast cancer classification, offering a promising tool for early detection and precise diagnosis.

KEYWORDS: Breast cancer · ResNet-50 model · transfer learning · Daubechies wavelet transform · mammography · wavelet transform.

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تصنيف اورام الثدي باستخدام تقنية الذكاء الاصطناعي ResNet-50 وتطبيق تقنية المويجات Wavelet لتحليل الصورة كمعالجة اولية .

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الملخص

سرطان الثدي هو مرض منتشر ومعقد يتطلب تشخيصاً و تصنيفا دقيقا في الوقت المناسب والعلاج الفعال. تقترح هذه الورقة نظام تصنيف سرطان الثدي الذي يستفيد من نموذج ResNet-50ويتضمن نقل التعلم (Transfer Learning). يستخدم النظام نموذجين منفصلين من طراز :ResNet-50 أحدهما للتصنيف الطبيعي وغير الطبيعي والآخر لتصنيف الأورام الحميدة والخبيثة ضمن الفئة غير الطبيعية. يستخدم التقييم التجريبي ثلاث قواعد للبيانات MIAS :، DDSM، و.CBIS-DDSM يتم تطبيق تقنية تحويل المويجات (Wavelet) كخطوة ما قبل المعالجة لتحسين صور التصوير الشعاعي للثدي. ويحقق النظام أداءً متميزاً بدقة عالية تصل إلى 99.48% و99.25% للنموذجين الأول والثاني على التوالي. بالإضافة إلى ذلك تم الحصول على قيم حساسية ونوعية تصل إلى 99.32% و99.17% للنموذج الأول و99.07% و98.89% للنموذج الثاني. والجدير بالذكر أن مجموعة بيانات DDSMتتفوق باستمرار على مجموعات البيانات الأخرى في كلا النموذجين. يوضح النظام المقترح فعالية نموذج ResNet-50 وتقنية تحويل المويجات في تصنيف سرطان الثدي، مما يوفر أداة واعدة للكشف المبكر والتشخيص الدقيق.

الكلمات المفتاحية : سرطان الثدي , نموذج الشبكات العصبية ResNet-50 , انتقال التعليم , تحويلة المويجات Daubechies , تصوير ماموجرام , تحويلة المويجات.

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1. INTRODUCTION

Artificial Intelligence (AI) (Ramesh, A. N., et al.,2004) is a rapidly evolving field of computer science that focuses on creating intelligent systems capable of performing tasks that traditionally require human intelligence. It encompasses various techniques and approaches such as machine learning, deep learning, and natural language processing. AI has widespread applications across industries, including healthcare, finance, transportation, and automation, with the potential to revolutionize how we work, live, and interact with technology in the future.

Breast cancer (Scully, Olivia Jane, et al.,2012) is the most common cancer among women worldwide, accounting for a significant number of cancer-related deaths. Early detection andaccurate classification of breast cancer play a crucial role in improving patient outcomes and guiding appropriate treatment strategies. With the advent of deep learning techniques, there has been a surge of interest in developing robust and efficient models for breast cancer classification using medical imaging data. Deep learning has shown remarkable success in various domains, including computer vision and natural language processing. In the field of medical image analysis, deep learning models have demonstrated their potential in accurately diagnosing and classifying diseases. Convolutional Neural Networks (CNNs), a type of deep learning architecture, have proven particularly effective in extracting intricate features from medical images. Residual Neural Networks (ResNet), a specific type of CNN architecture, have gained considerable attention due to their ability to overcome the challenges associated with training extremely deep networks. The fundamental innovation of ResNet lies in the concept of residuallearning, which allows for the successful training of networks with hundreds oflayers while mitigating the vanishing gradient problem.

This unique characteristic makes ResNet an appealing choice for breast cancer classification tasks, whereaccurate detection

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of subtle patterns and features in medical images is crucial. In this paper, we provide an indepth overview of the application of ResNet inbreast cancer classification. We aim to explore the strengths and potential of ResNet models in improving the accuracy and efficiency of breast cancer diagnosis. By reviewing the existing literature and state-of-the-art studies, we aim to identify the key advancements, challenges, and opportunities in this field. Theavailability of large-scale and well-annotated breast cancer imaging datasets is crucial for training ResNet models effectively. We discuss the importance of diverse and comprehensive datasets and highlight the significance of appropriate preprocessing techniques to enhance model performance. Throughout the paper, we analyze and compare different variants of ResNet, such as ResNet-50, ResNet-101, and ResNet-152, in the context of breast cancer classification. We examine their architectural characteristics, strengths, and applications, considering their performance and computational requirements. By reviewing the state-of-the-art studies that have employed ResNet for breast cancer classification, we aim to provide insights into the methodologies, performance metrics, and validation strategies employed. We identify the challenges faced by researchers in this domain and discuss potential avenues for further improvement and future research directions. In the following sections of this paper, we delve into the foundational concepts of deep learning, provide an overview of ResNet, discussbreast cancer imaging datasets, examine data preprocessing techniques, reviewthe state-of-the-art studies, and highlight the implications and future directionsfor the application of ResNet in breast cancer classification.

2. RELATED WORK

There has been extensive research conducted on breast cancer detection and diagnosis. Specifically, we will focus on studies that have employed deep transfer learning techniques on mammogram images to address this issue.

A study by (A. Khamparia, S. Bharati, P. Podder, D. Gupta, A. Khanna, T. K. Phung, and D.N. H. Thanh, 2021) introduced the MVGG architecture, achieving an accuracy of 89.8%.

The authors then developed a hybrid transfer learning model by combining MVGG with ImageNet, resulting in an accuracy of 94.3%. Their work utilized the DDSM database. In another study (Rasheed, M. S. Younis, J. Qadir, and M. Bilal, 2021), the authors proposed a system that significantly improved the accuracy of Mini-MIAS detection. They employed a preprocessing approach involving augmentation, segmentation, andwavelet transformation, which facilitated transfer learning in neural networks.They achieved a normal class AUC of 99% and an abnormal class AUC of 97%.In (Saber, M. Sakr, O. M. Abo-Seida, A. E. Keshk, and H. Chen,2021), researchers presented a novel deep learning model for automatic detection and classification of breast cancer using the transfer learning technique. Their experiments with the Mini-MIAS database demonstrated that VGG16 wasthe most suitable model for breast cancer detection, achieving high accuracy,sensitivity, specificity, precision, F-score, and AUC. The 80-20 method yieldedaccuracy of 98.96%, sensitivity of 97.83%, specificity of 99.13%, precision of97.35%, F-score of 97.66%, and AUC of 99.5%. The 10-fold cross-validation method yielded accuracy of 98.87%, sensitivity of 97.27%, specificity of 98.2%, precision of 98.84%, F-score of 98.04%, and AUC of 99.3%.

Additionally, in (E. L. Omonigho, M. David, A. Adejo, and S. Aliyu, 2020), authors proposed a modified version of the AlexNet deep convolutional neural network model for detecting breast cancers in mammography. Their aim was to enhance categorization accuracy by utilizing augmentation techniques. They achieved an accuracy of 95.70% by adapting the pre-trained AlexNet model to classify mammography images into normal and abnormal categories. Lin Dong and Kohei Inoue (L. Dong and K. Inoue, “Diagnosis of breast cancer from mammogram images based on cnn, 2020) developed a breast cancer diagnosis systemby leveraging transfer learning and data augmentation techniques, utilizing an updated version of AlexNet and LeNet. Their proposed system achieved an impressive accuracy of 91.4%. In another study (S. A. Agnes, J. Anitha, S. I. A. Pandian, and J. D. Peter,2019), a Multiscale All Convolutional Neural Network (MA-CNN) was employed to classify mammography images into normal, benign, and malignant categories. With a sensitivity of 96%, the authors utilized the Mini-MIAS database and improved the accuracy of the classification system by incorporating multiscale filters to capture a broader range of contextual information.

3. METHODOLOGY

3.1 METHOD OVERVIEW

In this study, two ResNet-50 models are utilized for different purposes in breast cancer detection:

- The first ResNet-50 model is employed for the classification of normal and abnormal cases as shown in Figure (1).

- The second ResNet-50 model is specifically designed for distinguishing between benign and malignant cases as shown in Figure (1).

The research process involves the utilization of three datasets, namely **MIAS**, **DDSM**, and **CBIS-DDSM**, and incorporates the wavelet transform technique as a preprocessing step. By using these datasets and applying the ResNet-50 models, the study aims to develop a robust system that accurately identifies normal and abnormal breast cancer cases, as well as accurately differentiates between benign and malignant tumors.

The ultimate goal of this research is to contribute to the field of breast cancer detection by providing a reliable and effective system that aids in early diagnosis, leading to improved patient outcomes. The findings highlight the potential of the ResNet-50 models and the wavelet transform preprocessing technique in enhancing the accuracy of breast cancer

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classification, enabling timely interventions and appropriate treatment decisions.

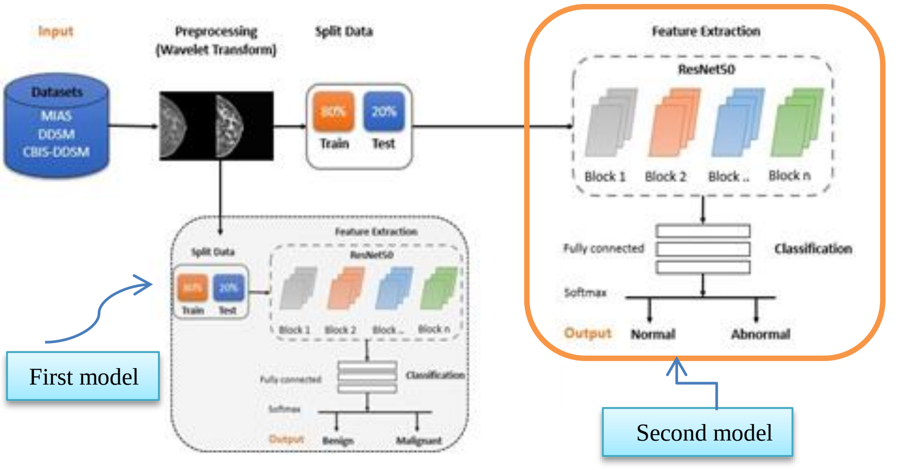

Figure 1: Diagram of proposed models structure.

3.2 DATA ACQUISITION

The data acquisition process plays a crucial role in training and evaluating the breast cancer classification system. In this study, three primary datasets are utilized: The Mammographic Image Analysis Society (MIAS) database (Suckling, John, et al.,2015), the Digital Database for Screening Mammography (DDSM) (Lévy, Daniel, and Arzav Jain.,2016), and the Curated Breast Imaging Subset of DDSM (CBIS-DDSM) (Falconi, Lenin G., et al.,2020).

The MIAS database contains a collection of mammography images, along with corresponding annotations such as breast density and abnormality labels. These images provide valuable insights into different breast cancer cases and serve as a foundation for training and testing the classification system.

The DDSM dataset is a comprehensive repository of mammography images specifically designed for screening purposes. It offers a diverse range of images from different screening centers, facilitating the development and evaluation of breast cancer classification algorithms.

The CBIS-DDSM subset is a curated collection derived from the DDSM dataset, focusing on high-quality mammography images with accurate annotations. This subset ensures a standardized and reliable dataset for training and validating the classification system.

3.2 DATA PROCESSING

In the breast cancer classification study, an additional technique called wavelet transform (Yoo, Jaejun, et al.,2019) is utilized as a preprocessing step to enhance mammography images as shown in Figure(2). Specifically, the wavelet transform is applied using the wavelet filter knownas Daubechies, which allows for a four-level decomposition of the images.

The wavelet transform plays a crucial role in improving the quality and discriminative power of the data by decomposing the images into different frequency components. This decomposition helps capture relevant patterns and structuresat various scales, enabling a more comprehensive analysis of the breast tissue.By highlighting important features while reducing noise, the wavelet transform enhances the representation of the mammography images. The enhanced representation obtained through the wavelet transform serves as valuable input for the subsequent classification model. It provides a more informative and refined dataset that aids in accurately distinguishing between normal and abnormal breast tissue. This pre-processing technique significantly contributes to the overall performance of the breast cancer classification system, leading to more accurate detection and diagnosis of breast cancer cases.

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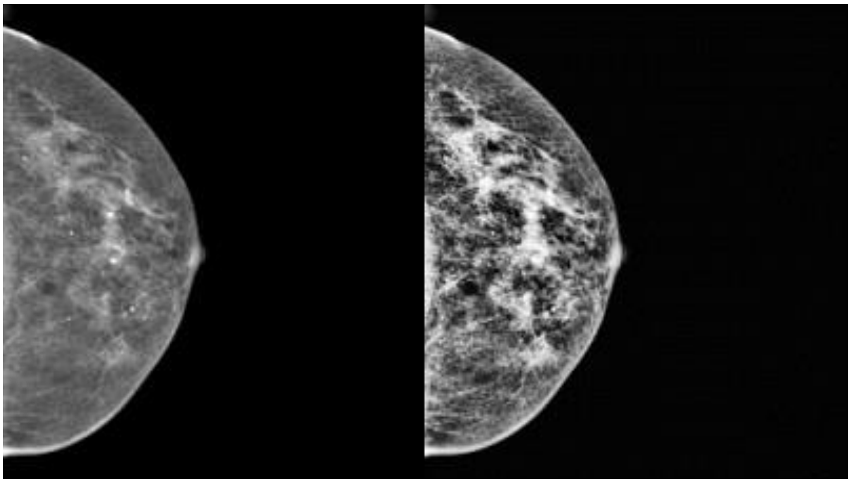

Figure 2: Mammogram image with preprocessing de-noising effect.

3.4 PROPOSED MODELS

ResNet-50 is a deep neural network architecture that revolutionized the field of computer vision. It employs a unique combination of 3x3 and 1x1 convolutional filters to extract features from the input data. The architecture is composed of multiple blocks, each containing several residual units. These residual units utilize skip connections, also known as identity mappings, to add the original input to the output of each unit. This innovative design allows ResNet-50 to overcome the challenges of training deep networks by alleviating the vanishing gradient problem and enabling effective information flow through the network.

The utilization of skip connections in ResNet-50 is a key factor in its success. By preserving the original input and adding it to the output of subsequent layers, ResNet-50 can capture and propagate important information that might have been lost or degraded in deeper layers.

Transfer learning (Yoo, Jaejun, et al., 2019) is a machine learning technique that leverages the knowledge gained from solving one problem to improve the performance on a different but related

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problem. In the context of deep learning, transfer learning involves utilizing pre-trained models that have been trained on large-scale datasets, suchas ImageNet, and adapting them to a specific task or domain.

The main idea behind transfer learning is that the learned feature representations in the pre-trained model can capture general visual patterns and semantic knowledge that are transferable across different tasks. By initializing a model with pre-trained weights, the model starts with a good set of initial parameters that have already learned to extract meaningful features from images. ResNet-50 is a powerful convolutional neural network architecture widely used for image classification tasks, including breast cancer classification. With a depth of 50 layers, ResNet-50 incorporates residual connections to address the challenge of training deep networks. These residual connections enable the direct flow of gradients and preserve important features, allowing the network to effectively learn complex representations.

During the training phase, the model's weights are fine-tuned using the breast cancer dataset, such as the MIAS database, DDSM, or CBIS-DDSM, ensuringthat the model adapts to the specific characteristics of breast cancer images. This fine-tuning process adjusts the model's parameters to optimize its performance for breast cancer classification. The model is trained using an appropriate optimization algorithm, such as stochastic gradient descent (SGD) or Adam, and a suitable loss function, such as cross-entropy loss, to measure the discrepancy between predicted and true labels. The training process involves iteratively updating the model's weights based on the gradients calculated through backpropagation. By incorporating the ResNet-50 architecture and leveraging transfer learning, the proposed model benefits from both the depth and the pre-learned representations of the network. This allows for robust and accurate classification of breast cancer images, ultimately

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contributing to improved diagnosis and treatment decisions in the field of breast cancer.

In our proposed model for breast cancer classification, we introduce a system that incorporates two separate ResNet-50 models. The first ResNet-50 model is dedicated to the classification of normal and abnormal cases using the mammography images as input. The second ResNet-50 model, employing the same set of parameters, is designed specifically for the classification of benign and malignant cases. This dual-model approach allows for more precise and targeted classification, enhancing the overall accuracy of the system. By decomposing the images with the wavelet transform and applying two separate ResNet-50 models, our proposed system provides a comprehensive framework for breast cancer classification, facilitating early detection and appropriate treatment decisions.

4. EXPERIMENTAL RESULTS

The breast cancer classification experiment utilized a computer with 8GB of RAM and an Intel i5 processor, running on Google Colab. This hardware and cloud-based platform combination supported data loading, preprocessing, and model training efficiently. Google Colab provided access to essential TensorFlow libraries for deep learning tasks.

The 8GB RAM capacity accommodated the large image dataset and memory-intensive processes. The Intel i5 processor, though its specific details were unspecified, is recognized for its performance and versatility, making it suitable for machine learning in the Colab environment.

While processor generation and clock speed weren’t specified, i5 processors are generally adept at handling demanding computational tasks. In summary, this setup, comprising 8GB RAM, an Intel i5 processor, and Tensor Flow libraries in Google Colab, ensured a robust computational environment for breast cancer classification model training and evaluation.

The ResNet-50 model shows a better performance on the DDSM datasets compared to other datasets. The system was trained for 20 epochs with a batch size of 32 using transfer learning.

In the first model, which classified images into normal and abnormal categories, the DDSM dataset exhibited outstanding performance, contributing tothe achieved accuracy of 99.48%. The sensitivity of 99.32% and specificity of 99.17% as shown in Figure(3) further underscored the effectiveness of the DDSM dataset in accurately identifying normal and abnormal cases.

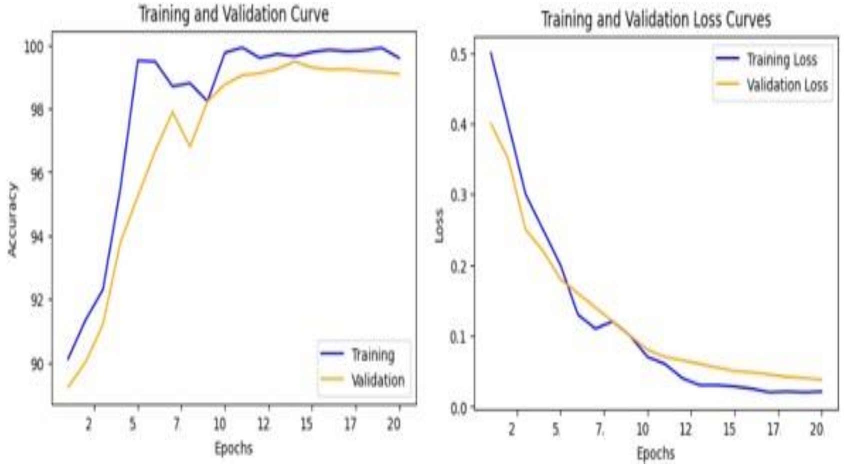

Figure 3: Accuracy and Loss of the trained model 1.

Similarly, in the second model designed for distinguishing between benign and malignant cases within the abnormal category, the DDSM dataset demonstrated superior performance. The achieved accuracy of 99.25 %, a sensitivity of 99.07% and a specificity of 98.89% as shown in figure (4) highlighted the dataset's effectiveness in accurately identifying malignant cases.

These high sensitivities and specificities demonstrate the robustness and accuracy of the ResNet-50 model in capturing and learning discriminative features relevant to breast cancer diagnosis. The experimental results highlight the potential of the proposed system in assisting healthcare professionals with accurate and precise classification of breast cancer cases, enabling effective treatment decisions.

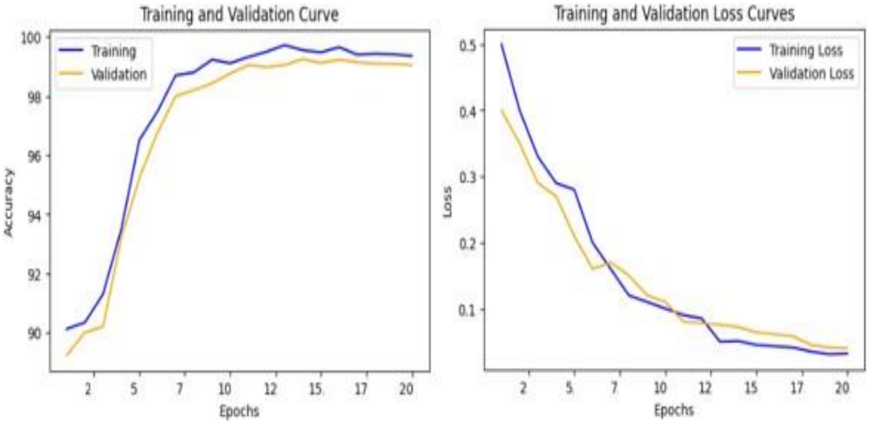

Figure 4: Accuracy and Loss of the trained model 2.

By achieving such high sensitivities and specificities, the system enhances the early detection of breast cancer and contributes to more accurate diagnoses. This, in turn, leads to improved patient outcomes and more efficient healthcare practices.

The utilization of transfer learning, combined with the ResNet-50 model,enables the system to leverage pre-existing knowledge from large-scale datasets, reducing the need for extensive training epochs while still achieving exceptional accuracy and performance. This makes the proposed system a valuable tool for breast cancer classification and diagnosis.

To evaluate our model we used the following metrics: accuracy, specificity, and sensitivity as depicted by the equations (1), (2), and (3) where TP is the true positive, TN is the true negative, FP is the false positive and FN is the false negative.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TN + FP + TP + FN}} \times \mathbf{100} \ldots\ldots\ldots\ldots..(\mathbf{1})$$

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$$Specificity = \frac{TN}{TN + FP} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

We have obtained the confusion matrix Figures(5)(6) for our models, which serves as a solidconfirmation of its performance. The confusion matrix allows us to assess how well the models are classifying instances by providing a breakdown of predicted and actual class labels.

In Tables 1 and 2, we provide a detailed presentation of the performance achieved by the breast cancer classification system using the ResNet-50 modelon different datasets. These tables allow for a comprehensive comparison of the accuracy, sensitivity, and specificity obtained for each dataset, shedding light on the system’s performance across various scenarios.

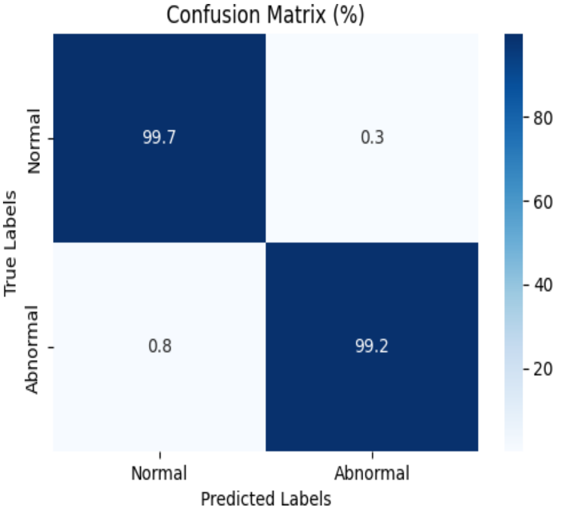

Figure 5: Confusion Matrix of model 1.

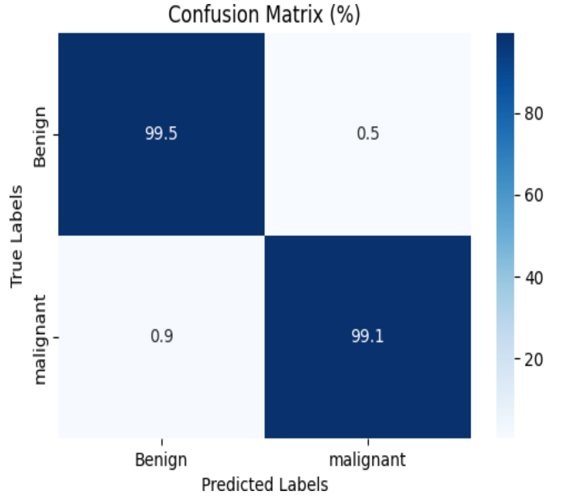

Figure 6: Confusion Matrix of model 2.

Table 1 specifically focuses on the classification of mammography imagesinto normal and abnormal categories. The accuracy, sensitivity, and specificity values for each dataset, including MIAS, DDSM, and CBIS-DDSM, are displayed individually. This allows researchers and healthcare professionals to assess the system's performance on each dataset and identify any variations or trends.

Similarly, Table 2 emphasizes the system's capability to differentiate between benign and malignant cases within the abnormal category. By presenting the accuracy, sensitivity, and specificity metrics for each dataset, such as MIAS, DDSM, and CBIS-DDSM, researchers can evaluate the ResNet-50 model's effectiveness in accurately identifying malignancy across different datasets.

Notably, the results highlight that the DDSM dataset consistently outperforms the other datasets in both models. The accuracy, sensitivity, and specificity achieved with DDSM demonstrate its effectiveness in providing a rich and diverse set of cases for training the ResNet-50 model. This suggests that the DDSM dataset captures the necessary characteristics and complexities of breast cancer, enabling the model to achieve superior performance.

TABLE 1. Comparison of datasets and performance metric s for model 1.

Dataset	Accuracy (%)	Specificity (%)	Sensitivity (%)
MIAS	98.7	98.41	98.56
DDSM	99.48	99.17	99.32
CBIS-DDSM	98.95	98.81	98.89

TABLE 2. Comparison of datasets and performance metrics for model 2.

Dataset	Accuracy (%)	Specificity (%)	Sensitivity (%)
MIAS	98.43	98.21	98.36
DDSM	99.25	98.89	99.07
CBIS-DDSM	98.75	98.63	98.69

5. CONCLUSION

The breast cancer classification system leveraging the ResNet-50 model demonstrated exceptional performance in accurately classifying mammography images into normal, benign, and malignant categories. The system utilized transfer learning and was trained for 20 epochs with a batch size of 32. The experimental results, as depicted in Tables 1 and 2, showcased the effectiveness of the ResNet-50 model in breast cancer classification across different datasets. The DDSM dataset consistently outperformed other datasets in both models, high-lighting its superior quality and ability to capture the necessary features foraccurate classification.

The achieved high accuracy, sensitivity, and specificity values underscored the robustness of the system in distinguishing between normal and abnormal cases, as well as between benign and malignant cases within the abnormal category.

The utilization of transfer learning and the wavelet transform preprocessing technique contributed to the system's success in capturing and learning discriminative features relevant to breast cancer diagnosis.

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