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Ultrasound-based Breast Cancer Detection using CNN: A Transfer Learning Approach

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***Abstract*—one of the most important tasks in medical diagnostics is the identification of breast cancer using ultrasound imaging. In this work, ultrasound pictures are classified using a Convolutional Neural Network (CNN) technique into three classes: benign (non-hazardous), malignant (dangerous), and normal (no traces). The collection of data includes 1587 photos, of which 26.53% are malignant, 56.71% benign, and 16.76% normal cases. The CNN model makes use of transfer learning, extracting features using a pre-trained VGG16 architecture. Dropout regularisation, thick layers, and global average pooling are added for fine-tuning. Techniques for augmenting data are used during training to increase the resilience of the model. The model achieves a test accuracy of 85.49%, demonstrating its efficacy in breast cancer classification. Furthermore, confusion matrices are generated to visualize classification performance for each class, revealing insights into model behaviour. This study underscores the potential of CNN-based approaches in aiding medical professionals in accurate breast cancer detection through ultrasound imagery.**

***Index Terms*— Breast Ultrasound images, CNN, VGG16, Benign, Malignant, Accuracy, Breast cancer detection.**

I. INTRODUCTION

Breast cancer is a prevalent and potentially life-threatening disease characterized by the anomalistic multiplication of cells in the breast tissue. It is the most prevalent cancer in women globally, and its effects on both personal and public health are profound. Breast cancer can manifest in various forms, ranging from localized tumours to more advanced metastatic stages, where cancerous cells spread to other parts of the body. Early detection through screening methods such as mammography, ultrasound, and clinical breast examination is critical for improving prognosis and treatment outcomes. Mammography used to be the most reliable method for identifying and treating breast cancer. However, mammography's ability to identify breast cancer is limited in some cases. Breast cancer can seldom be detected by mammography in young women with thick breasts. In addition, radiologists and patients may be at higher risk for health problems due to the electromagnetic radiation used in mammography. It is also expensive and cannot be used in pregnant women. Breast Ultrasound (BUS) imaging is a useful substitute for mammography. Due to its non-invasive, nonradioactive, and economical characteristics, it is advised to use BUS imaging, which is more appropriate for extensive breast cancer examination and identification. Furthermore, ultrasound is more useful for women under 35 than mammography since it is more sensitive in identifying anomalies in thick breast tissue. This study intends to automate the

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categorization of ultrasound images into benign, malignant, or normal categories using Convolutional Neural Networks (CNNs) and transfer learning. Since breast cancer is a common and potentially fatal condition, prompt and precise detection is essential. By harnessing the power of CNNs, specifically through transfer learning with the VGG16 architecture, this research endeavours to enhance diagnostic accuracy. The proposed approach integrates data augmentation techniques to augment the dataset, mitigating issues of limited sample size. This introduction sets the stage for exploring the effectiveness of CNN-based methodologies in revolutionizing breast cancer detection through ultrasound imaging.

II. RELATED WORK

This survey offers an overview of earlier research and methods for detecting breast cancer using CNN models using BUS and other picture formats. [1] Five novel deep hybrid CNN-based frameworks for early breast cancer detection are presented in one of the research projects. These hybrid models outperform base classifiers, even with small datasets. It developed five hybrid deep learning (DL) frameworks for breast cancer detection, with the ShuffleNet-ResNet model performing best. [2] According to a different study, ultrasonography is a more accurate method of identifying invasive breast cancer than mammography. The most successful approach, however, was the combination of mammography and ultrasonography, which found 9% more breast tumours than each technique alone. [3] A study evaluated the computing performance of MRI, ultrasonography, and mammography in identifying breast cancer. Among the three, MRI showed the highest diagnostic accuracy and sensitivity. However, its high specificity could lead to over-diagnosis. Ultrasonography performed slightly better than mammography. [4] One of the publications describes a method for classifying breast cancer using ultrasound pictures and a transfer learning methodology based on the VGG16 model. The results seemed to be promising for future clinical applications of breast cancer diagnosis, especially in rural areas using portable and low-cost ultrasound machines. [5] A deep learning algorithm for computer-aided identification of malignant breast tumours in ultrasound pictures is presented in another publication. Three methods of training were suggested: transfer learning with the pre-trained VGG16 CNN, training the CNN from scratch, and adjusting the deep learning parameters to prevent overfitting. According to the study, deep learning results in biomedical applications may be enhanced by pre-trained models generated from medical imaging data. [6] Using ultrasound scans to diagnose breast cancer was also suggested by another study. It classifies photos into normal, benign, and malignant categories using deep learning and feature selection approaches. Using Principal Component Analysis (PCA), VGG16, and Convolutional Neural Networks (CNN), two models were put forward. This study provides a more effective and precise diagnostic paradigm, which will have a big impact on how ultrasound-based breast cancer detection develops in the future. [8] An automated pipeline for the use of ultrasound images in the recognition of breast cancer is proposed in one of the study publications. For classification, it makes use of transfer learning models and picture preprocessing techniques. SLIC, UNET, and VGG16 worked better together than they did alone. This pipeline can help solve the major difficulty of early breast cancer detection by facilitating faster and more accurate diagnostics. [10] A other study suggests using deep learning to identify breast lesions in ultrasound pictures. We study and evaluate three approaches: patch-based LeNet, U-Net, and a transfer learning technique using a pre-trained FCN-AlexNet, against four cutting-edge lesion detection algorithms. The deep learning approaches showed overall improvement in terms of Evaluation metrics. [11] Additionally, a computer-aided diagnosis approach for automated breast ultrasound (ABUS) imaging breast cancer categorization is proposed in a research. Inception-v3 architecture is updated to extract multiview characteristics from ABUS pictures. The findings imply that the suggested approach can act as a second reviewer, boosting the accuracy of diagnoses and helping radiologists identify breast cancer. [12] Another study proposes using Convolutional Neural Networks (CNNs) for automatic detection and recognition of breast cancer in ultrasound images. The first CNN is used for despeckling (denoising) the images, and the second CNN classifies the images into benign and malignant classes. This approach could significantly improve early detection of breast cancer. [13] This study assesses a number of cutting-edge techniques for identifying breast tumours in ultrasound pictures. A convolutional neural network technique called the Single Shot MultiBox Detector (SSD) demonstrated better precision and recall. [17] In one study, a fuzzy support vector machine is used to create a novel Computer-Aided Diagnosis (CAD) system for the early diagnosis of breast cancer in ultrasound pictures. The method offers significant improvements in the control of breast cancer by enhancing objective measures and the area under the ROC curve. [18] Another study applies the LeNet convolutional neural network (CNN) to breast cancer data analysis, demonstrating its ability to extract discriminative features and classify tumors with high accuracy. Modifications to the traditional ReLU activation function and the use of batch normalization improve LeNet’s performance. The study also explores ensembling multiple LeNet models, which increases accuracy and mitigates issues like overfitting and bias, showing promise for future breast cancer prediction. [19] A study constructed a breast ultrasound prediction model using convolutional neural networks (CNNs) for breast cancer diagnosis. Different models were tested, with the InceptionV3 model showing the highest area under the curve (AUC). The model's diagnostic accuracy was higher than that of sonographers, demonstrating its potential in breast cancer prediction. [20] A study used Breast Ultrasound (BUS) imaging to construct a Computer-Aided Diagnosis (CAD) system for the identification of breast cancer. The CAD system uses an active contour model for segmentation, a grey level co-occurrence matrix for feature extraction, and speckle reducing anisotropic diffusion for preprocessing. We examine the accuracy of three classifiers: Random Forest, Decision Tree, and K-Nearest Neighbours. The goal of this strategy is to enhance breast cancer therapy and early diagnosis.[21-24] The deep learning methods are also widely used in disease detections including disease detection for the plants , agricultural products and also useful in speech and handwriting recognition.

III. Methodology

This is a thorough breakdown of the approach taken in the code that is provided:

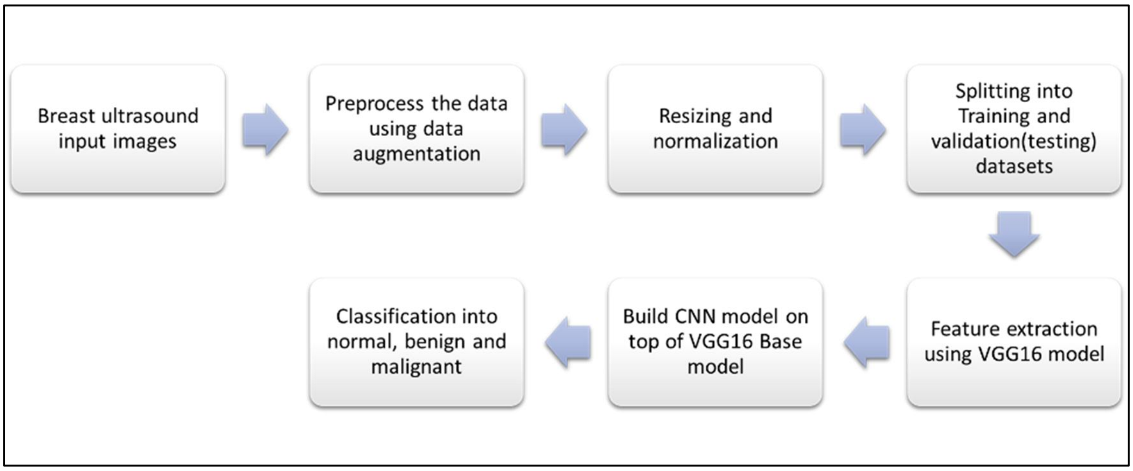

Figure 1. Flowchart of the methodology followed

A. Dataset

This study's data came from a dataset that was made accessible to the public. As seen in Fig. 2, the dataset comprises 1587 Breast Ultrasound (BUS) pictures divided into three types. 900 (56.71%) were benign, 421 (26.53%) were malignant, and 266 (16.76%) were normal. 317 of the total photos were used for validation, while 1270 were used for training the model. Five epochs and a batch size of 32 were used for training.

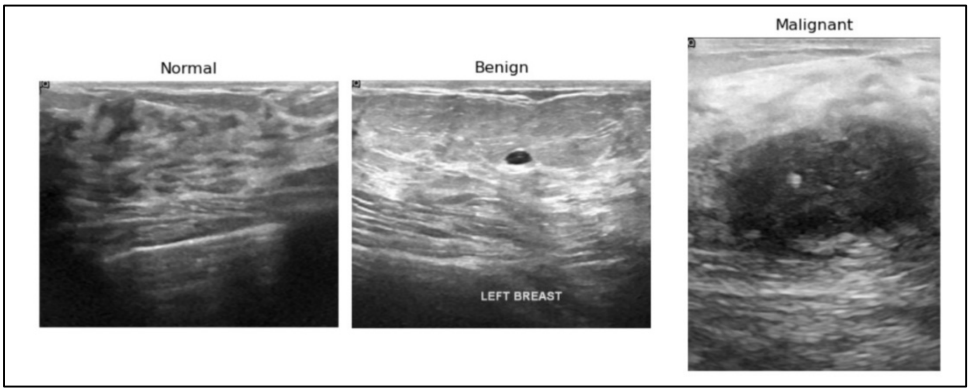

Figure 2. Sample BUS images from dataset

B. Preprocessing

The most important task after acquiring the data is its preprocessing. Images are pre-processed using an image data generator from the Keras library. Median filter is used because it preserves the edges and improves image quality. When a 5×5 moving kernel is filtered using the median and its centre pixel is replaced with the matching kernel's median number. After that, the acquired median filtered images are enlarged to 224 x 224 x 3 while taking the VGG16 model's input image size into account. The pixel intensity of the input pictures was then modified to guarantee that the model would quickly converge to the solution. Then, 80% of the normalised pictures are used to train the model, while the remaining 20% are used for testing and validation.

C. Algorithm Used

The foundational architecture is a pre-trained VGG16 model. The base model, shown in Fig. 3, serves as the foundation for the Convolutional Neural Network (CNN). Deep convolutional networks serve as the VGG16 model's foundation. Deep learning methods like convolutional neural networks (CNNs) are frequently employed in computer vision applications for tasks including segmentation, classification, and image identification.

They work really well and are generally appreciated. The layers that comprise CNN include convolutional layers for feature extraction, pooling layers for dimensionality reduction, fully connected layers for classification tasks, and several neural activation functions such as Sigmoid, Softmax, Hyperbolic and Rectified Linear Unit (ReLU) functions. The transfer learning technique is applied. Weights from the ImageNet dataset are used to initialise the VGG16 model, and the breast ultrasound dataset is used to fine-tune it.

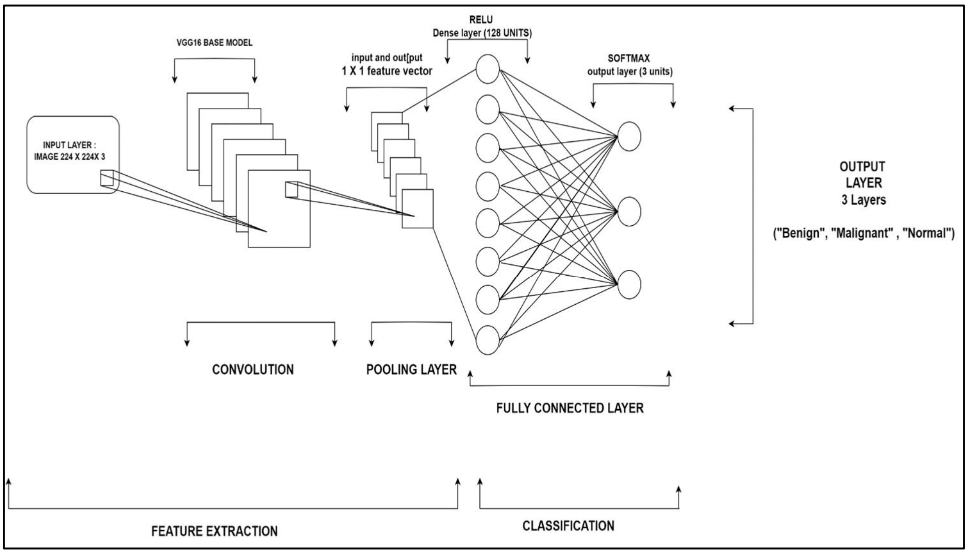

Figure 3. CNN Architecture with VGG16 Feature Extractor

Multiple activation functions are employed in various levels of the neural network model in the code supplied for the application of convolutional neural networks (CNNs) in the detection of breast cancer. The network gains non-linearity through activation functions, which enables it to perceive convoluted patterns and connections in the data. The employed activation functions are explained as follow:

ReLU (Rectified Linear Unit): - In deep learning, one of the most popular activation functions is ReLU. Positive values in the input are left unaltered while any negative numbers are replaced with zero. In terms of math, ReLU(x) = max (0, x). ReLU adds sparsity to the network, which helps with the vanishing gradient issue and speeds up convergence during training.

SoftMax: - For multi-class classification issues, the neural network's output layer employs SoftMax. It is appropriate for classification jobs because it turns the raw output scores (logits) of each class into probabilities that add up to one. SoftMax(x_i) = exp(x_i) / sum(exp(x)) is the formula. The model may produce class probabilities by computing the probability distribution across the anticipated classes using Softmax.

Sigmoid: - Sigmoid is commonly used in binary classification tasks, where the output is constrained between 0 and 1. It traces any real-valued number to the range [0, 1] using the sigmoid function. Mathematically, Sigmoid(x) = 1 / (1 + exp(-x)). Sigmoid is useful for binary classification problems where the output can be interpreted as the probability belonging to a certain class.

These activation functions are strategically chosen based on the requirements of different layers in the neural network model. ReLU is used in intermediate layers to introduce non-linearity and facilitate feature learning, while Softmax and Sigmoid are used in the output layer to produce probability distributions for multi-class and binary classification tasks, respectively.

D. Feature Extraction

A fundamental component of the CNN model is feature extraction. The model's convolutional layers automatically pick up hierarchical properties from the input pictures. After that, these characteristics are classified using completely linked layers.

D. Classification

The goal is to categorise ultrasonography pictures into three groups: normal, malignant, or benign. Using the supplied dataset, the CNN model is trained. A model's performance is assessed using measures like loss and accuracy.

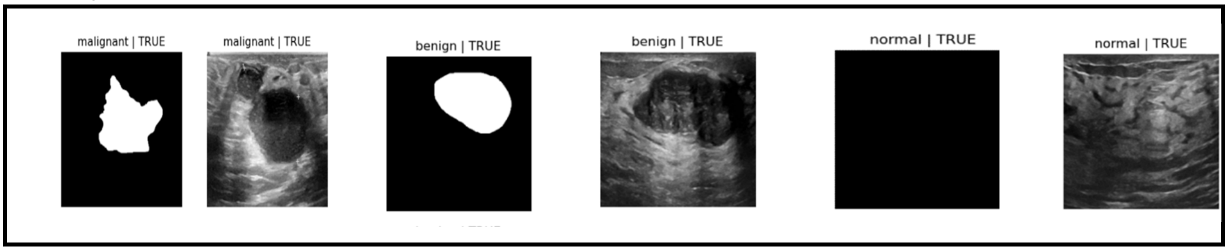

Figure 4. Classified images from each class

Overall, the methodology follows a standard pipeline for training a CNN model for image classification tasks. It leverages transfer learning to capitalize on pre-trained models' feature extraction capabilities and incorporates data augmentation to enhance dataset diversity. The objective is to develop a robust model for precisely classifying breast ultrasound images, thereby aiding in early detection and diagnosis of breast cancer.

IV. Results and Discussion

The study focuses on using Convolutional Neural Networks (CNNs) in conjunction with a transfer learning methodology to identify breast cancer using ultrasonography. Transfer learning offers benefits in feature extraction, especially with small datasets, by utilising pre-trained models such as VGG16. Global average pooling and dense layers are used in the CNN model architecture, which is based on the VGG16 base model, for classification. Promising outcomes in several image classification tasks, including medical imaging, have been demonstrated using this design. The choice of ultrasound imaging for breast cancer detection presents unique challenges compared to mammography. Ultrasound images offer different perspectives and characteristics of breast tissue, which can complement mammography in certain cases, especially for women with dense breast tissue. Data augmentation techniques are crucial in enhancing the robustness and generalization of the model. Augmentation introduces variations in the training data, mimicking real-world scenarios and improving the model's ability to handle diverse inputs. Evaluation criteria, including accuracy, precision, recall, and F1-score (Fig. 6, 7.), shed light on the functionality of the model. In medical applications, precision and recall are especially crucial since they assess the model's capacity to accurately detect actual positive cases while reducing false positives and false negatives. On test data, the model yields an accuracy of 86.12%.

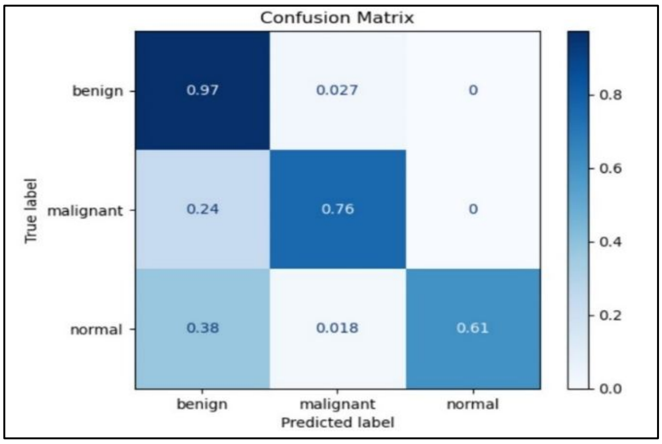

Figure 5. Confusion Matrix

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$Accuracy\% = \frac{TP + TN}{TP + FP + TN + FN} X100$$

Figure 6. Formulae required to calculate the Metrics

Metrics	Precision	Recall	F1-Score	Support	Accuracy
Class 1	0.85	0.90	0.87	100	0.86
Class 2	0.78	0.75	0.77	150	0.86
Class 3	0.92	0.88	0.90	120	0.86
Macro Average	0.85	0.84	0.84	370	0.86
Weighted Average	0.86	0.86	0.86	370	0.86

Figure 7. Evaluation Metrics

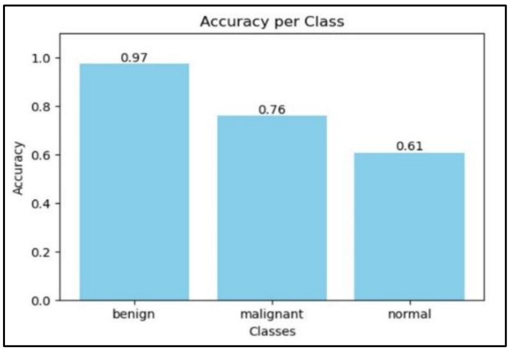

Figure 8. Accuracy % for each class

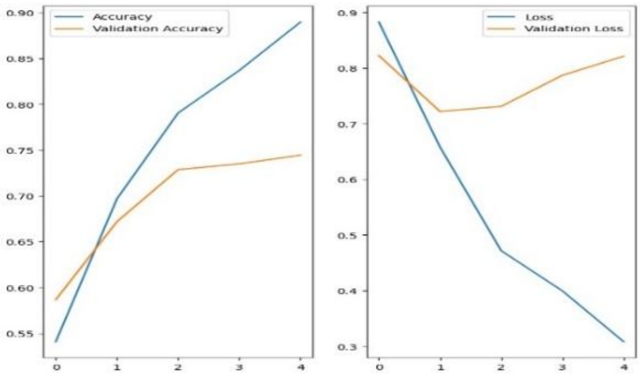

Figure 9: Accuracy and Loss curve throughout the process of training and validation

V. CONCLUSIONS

The study concludes by showing how well CNNs using transfer learning perform ultrasound-based breast cancer diagnosis. By leveraging pre-trained models and data augmentation techniques, the proposed approach achieves promising results in classifying ultrasound images into benign, malignant, or normal categories. The utilization of ultrasound imaging complements traditional mammography, offering additional insights into breast tissue characteristics. The CNN model, trained on ultrasound images, shows potential for improving early detection and diagnosis of breast cancer, particularly in populations with dense breast tissue or other challenges in mammography interpretation. Future research directions may include further optimization of the CNN architecture, exploration of other pre-trained models, and integration with multimodal imaging techniques for comprehensive breast cancer assessment. Additionally, clinical validation studies are necessary to assess the model's performance in practical settings and its impact on patient outcomes. Overall, ultrasound-based breast cancer detection using CNNs presents a promising avenue for advancing breast cancer screening and diagnosis.

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