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A Novel Ensemble Framework for Breast Cancer Detection using Ultrasound Imaging and Advance Augmentation Techniques

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Abstract

Breast cancer is a prominent form of cancer that is frequently detected and is a primary cause of mortality in women. Healthcare organizations prefer to utilize ultrasound imaging as the main method for detecting breast cancer due to its superior safety compared to other imaging techniques. Previous research mainly focused on handcrafted engineering, which is less accurate, time-consuming, and costly. However, we proposed a novel ensemble transfer framework for the early detection of breast cancer via ultrasound imaging. Three powerful transfer learning models such as VGG-16, EfficientNet-B2, and DenseNet-121 are utilized in the development of the ensemble framework. By employing transfer learning methodologies, the framework achieves enhanced computational efficacy in comparison to traditional deep learning approaches. The dataset for ultrasound breast imaging consists of three classes: normal, benign, and malignant. The use of cutting-edge augmentation techniques addresses the dataset's imbalance issues. The experimental findings indicate that the proposed framework demonstrates an accuracy rate of 99.74% in identifying breast cancer on the testing dataset, and it attained a testing loss of 0.013. The proposed framework has shown superior performance in comparison to existing studies.

Key Words: *Breast Cancer, Ensemble learning, Ultrasounds, Malignant cancer, Healthcare*

Introduction:

Cancer is one of the leading causes of death worldwide. It is characterized by the unrestrained and harmful proliferation of abnormal cells throughout the body. The two main forms of cancer are benign and malignant, which are classified based on their level of malignancy. The growth of benign cancerous cells is generally quite poor and without any malicious purpose. In contrast, cancerous cells are harmful, quickly increasing in number, and spread through blood vessels to infiltrate distant anatomical locations [1]. Women have a higher incidence of breast cancer, compared to men. According to the World Health Organization, 2.1 million women are affected by the potentially life-threatening condition breast cancer. Breast cancer is a prevalent malignancy among women, originating in the breast and subsequently metastasizing to other organs [2]. Breast cancer is the second most prevalent malignancy on a global scale, following lung cancer, and its primary site of involvement is the mammary tissues [3].

A wide range of imaging devices is easily available to assist in the early identification and treatment of breast cancer. Ultrasound of the breast is a commonly used diagnostic technique in clinical settings. Ultrasound is the primary modality for detecting breast cancer, and the findings of an investigation are examined using statistical methods. Ultrasound monitoring alters the behavior of breast cancer, shifting it from predominantly big, conspicuous lesions to smaller, occasionally benign cancer. Ultrasound is easy to use, secure for women, and radiation frees [4]. Computer-aided diagnosis (CAD) is a technical advancement that helps radiologists and other medical practitioners make accurate diagnoses. It enhances their capacity to recommend and advise on suitable drugs and therapies for the patient's treatment. Research findings indicate that cardiac angiography has improved sensitivity and specificity for detecting cancer. CAD has the capacity to significantly reduce the duration needed for image interpretation by radiologists and other healthcare practitioners [5]. CAD utilizes factors such as age, familial history, and breast density to produce a personalized risk evaluation. The findings of this examination can help inform decisions regarding monitoring and the course of therapy. The use of CAD is quite beneficial in the examination of breast cancer. It improves the precision of identifying breast cancer, reduces the need for unnecessary biopsies and therapies, and provides personalized risk evaluations [6].

Deep learning architectures, which can read complex representations, may be able to detect and classify breast cancer at an earlier stage, reducing the amount of effort spent on false positives and false negatives and thereby contributing to the prevention of different diseases. A lot of progress has been made in the fields of computer vision, deep learning, and medical image processing [7]. The prediction and treatment of patient outcomes based on individual features are made possible through the utilization of deep learning architectures. In order to detect and classify breast cancer, radiologists and pathologists need to devote a considerable amount of time and effort to the process. Deep learning networks can automate a variety of diagnostic activities, including the process of classifying lesions and analyzing images. It is possible that this will result in an improvement in productivity and a decrease in the chance of errors caused by humans. Deep learning networks are being applied in breast cancer analytics with the purpose of enhancing the accuracy, efficacy, and individualized care in the detection, diagnosis, and treatment of the disease. The four important contributions of our study are as follows:

- A new approach for automated breast cancer diagnosis is showcased by combining three powerful transfer learning VGG-16, EfficientNet-B2, and DenseNet-121 models. Through the utilization of transfer learning techniques, the framework attains improved computing efficiency as compared to conventional deep learning methods.
- The proposed ensemble architecture effectively differentiates between malignant and benign breast cancer using ultrasound data.
- Advance data augmentation is employed to enhance the efficacy of the model and minimize the issue of overfitting.
- The proposed model becomes more robust via a 10-fold cross-validation and comparison analysis with previous studies.

Literature Review:

This study introduces a novel deep learning model called DeepBraestCancerNet, which aims to detect and classify breast cancer with high accuracy. The suggested architectural design comprises a total of twenty-four layers: six convolutional layers, nine inception modules, and one completely linked layer. In addition, the design incorporates two normalization techniques, namely batch normalization and cross-channel normalization, alongside the truncated and leaky ReLu activation functions. According to the data, the recommended model has the highest classification accuracy. Furthermore, the authors evaluated the efficacy of the DeepBraestCancerNet method in comparison to numerous established DL models. Experiment results demonstrated that the suggested model exhibited superior performance compared to the prevailing leading models. Furthermore, they utilized an additional frequently employed dataset to validate the proposed model [8].

The main objective of the study [9] was to develop a state-of-the-art deep learning technique called CNN for the purpose of creating a computer-aided diagnostic (CAD) system. The system's goal was to accurately classify benign and malignant breast cancers using ultrasonography. They investigated by generating a heat map that visually represented the specific locations used by CNN to accurately categorize human malignancy and benignity. The Japan Association of Breast and Thyroid Sonology conducted a thorough clinical study from which the clinical data came. An ultrasound probe imaged 1536 breast masses in total, of which 897 were malignant and 639 were benign. Images were taken of each breast tumor from various perspectives. By fine-tuning the VGG19 and ResNet152 CNN models using balanced training data and augmentation, we created an ensemble network. This ensemble network utilized the mass-level classification strategy, enabling CNN to classify a specific mass by considering all available views.

Another study analyzes ultrasound images to detect breast cancer using pre-trained convolutional neural network models. To be more specific, they enhanced the pre-trained models by including a classifier in the top layer, allowing them to extract important features from ultrasounds. The accuracy of seven well-known, cutting-edge pre-trained models was evaluated using fivefold cross-validation. When training these models, several optimizers and hyperparameters were used. Furthermore, we evaluate the models' performance in utilizing Grad-CAM and occlusion mapping approaches to extract crucial information from ultrasound images for the purpose of cancer detection [10]. The authors in study [11] comprehensively evaluate the accuracy with which different state-of-the-art object identification technologies presently in use detect breast malignancies. In pursuit of this objective, the authors assembled a novel dataset comprising 464 cases of malignant lesions and 579 instances of benign lesions, accompanied by the corresponding ultrasound images, and enlisted the expertise of seasoned medical professionals to interpret the data. Several experiments show that the Single Shot MultiBox Detector (SSD), a new method based on convolutional neural networks, is better at recall and accuracy than other methods that have been used for a long time.

The objective of the work [12] was to provide a methodology for the identification and diagnosis of breast cancers through the analysis of ultrasound images. Six methods for identifying and classifying ultrasound images helped achieve this goal. The fractal approach was employed for the extraction of features from photographs. Furthermore, images were classified using several classification algorithms, such as KNN, NB, DT, SVM, and others. Subsequently, the CNN structure was purposefully crafted to classify breast cancer observed in ultrasound images. The suggested model achieved a 99.8% accuracy rate on the training set. The diagnosis validation demonstrates a sensitivity of 88.5% based on the test findings.

This research presents a new method for classifying ultrasound-detected breast cancer. Modern deep learning techniques form the basis of this system, which incorporates the best-selected qualities. There were five main components to the suggested framework: In order to improve the learning of CNN models, the following steps are taken: (i) Add more data to the initial dataset; (ii) Change the output layer of a DarkNet-53 model that has already been trained to include classes from the new dataset; (iii) Use transfer learning to train the changed model, getting features from the global average pooling layer; and (iv) Pick the best features using two improved optimization algorithms k [13]. Progress in deep learning has significantly enhanced the ability to recognize and classify objects. This research aims to assess the performance of several state-of-the-art object detection and classification algorithms when applied to breast lesion CAD. To do this, we acquired a brand-new dataset with 579 non-cancerous lesions and 464 cancerous lesions, along with the corresponding ultrasound images, which qualified medical professionals then evaluated. They did extensive experiments and assessed several deep learning architectures utilizing recently obtained dataset [14].

The authors provide an ultrasound dataset to the public, which consists of radio-frequency data from 39 subjects and segmentation templates created by two professionals. The Dice Score Coefficient values of 0.940.08 and 0.920.06, respectively, show that the segmentation maps exhibit a significant degree of consistency, both among and across observers. The Gated Shape Convolutional Neural Network can generalize better when the CutMix augmentation technique was used because it allows precise automatic layer segmentation of tissues [15]. The experimental results obtained from the mini-DDSM dataset [16] indicate that the proposed method exhibits superior performance in classification tasks. Specifically, it achieves 97.75% accuracy for malignancy detection and 99.17% accuracy for abnormality detection. In a similar vein, the accuracy rates achieved for abnormality and malignancy detection using the ultrasound dataset (BUSI) are 94.92% and 94.62%, respectively. When compared to benchmarking deep learning models, the suggested classifier performed better in terms of recognition rate. Breast picture identification has an accuracy percentage of 89.91%. Segmentation, feature extraction, classification, and tumor identification for breast cancer will all be areas where this model excels [17].

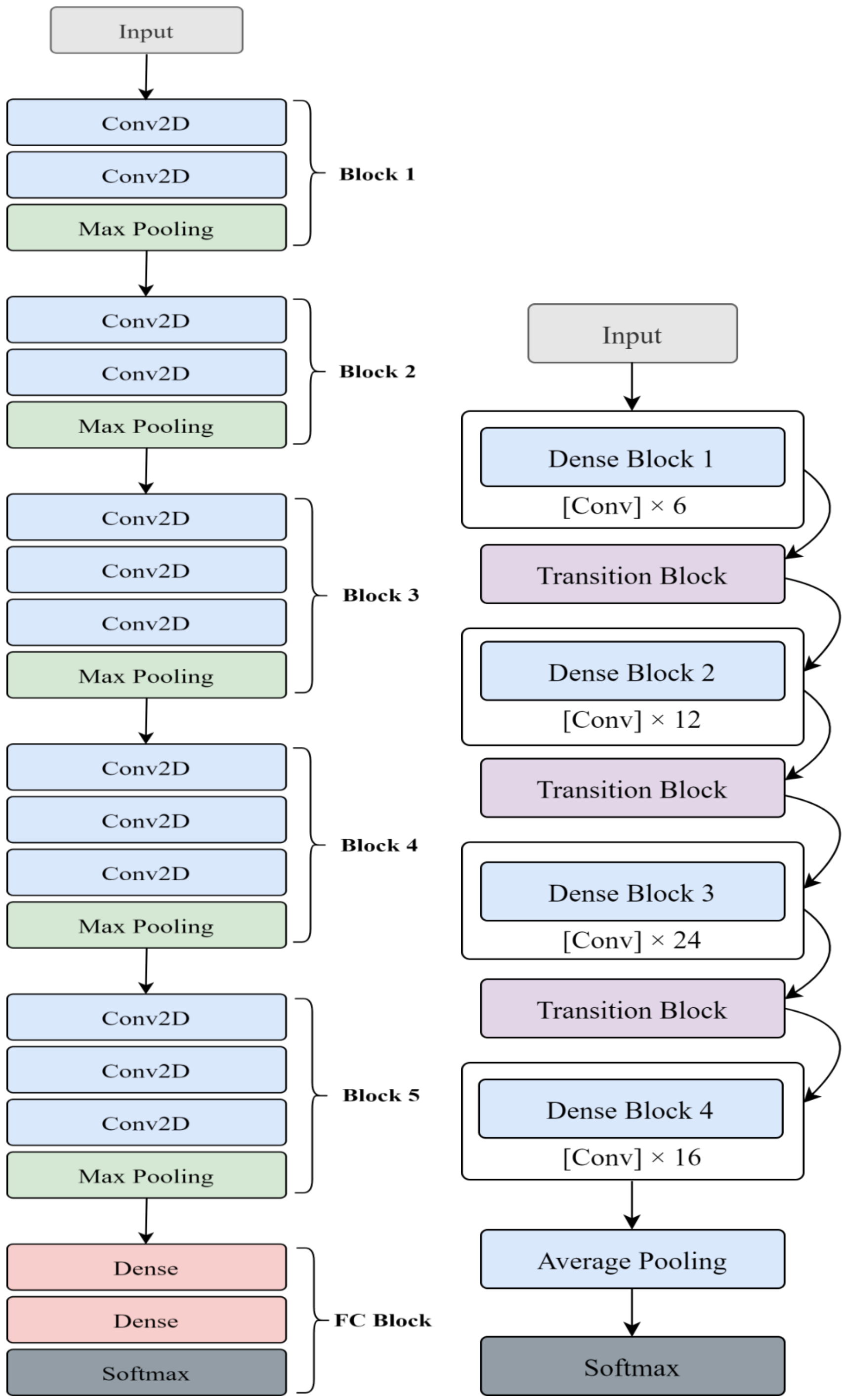
Materials and Methods:

Ultrasound Dataset:

The dataset consisted of breast ultrasound scans performed on women aged 25 to 75. In the afflicted cohort, 600 women individuals are present. The collection comprises a total of 780 images, each of which has average dimensions of 500 × 500 pixels. PNG files are utilized to store the images. As a result, the images are classified into benign, malignant, and normal categories. Gray scale ultrasonography images are frequently acquired. Estimated time is required to collect and label the scans.

Preprocessing:

Image preprocessing is very important in medical imaging. Deep learning needs a fixed-size input for processing. So, several tasks must be completed to render the dataset valuable. The dataset had redundant pictures that needed elimination. In addition, Baheya radiologists thoroughly examined and revised the inaccurate annotation. The DICOM images were transformed into PNG format using a specialized DICOM conversion program [18]. Following more refinement, just 780 photographs from the United States were left in the collection. The photos are classified into three categories: benign, malignant, and normal. The photographs were cropped to different dimensions to eliminate superfluous and insignificant borders [19].



(a) **(b)**

Fig. 1: (a) DenseNet-121 Architecture **(b)** EfficientNet-B2 Architecture

Augmentation:

To get desirable levels of generalization and accuracy, deep neural networks need a significant quantity of training data. At times, there may be an inadequate amount of image data available. Various tactics are employed to increase the training data in such situations. It creates training data by applying various operations, such as random rotation, shifts, shear, and rotations, to the input data. Image augmentation involves creating new images to train our deep learning model [20]. Manually gathering these extra images is superfluous as they are produced from the current training images. To execute rotation augmentations, just shift the image either to the left or right. The rotation degree parameter is primarily responsible for the safety of rotation augmentations. Cropping images may be a useful processing step for image data that has both height and width dimensions. This involves removing a central section from each image. Horizontal axis flipping is far more prevalent compared to vertical axis flipping [21]. Executing this enhancement is easy, and it has shown its value across several datasets. Split ratio before and after applying augmentation techniques is depicted in Tabe 1.

Table 1. Split ratio before and after applying augmentation techniques.

	Before	**After**	**Training**	**Testing**
Benign	891	1782	1426	356
Malignant	421	1684	1347	337
Normal	266	1330	1064	266
Total	1578	4796	3837	959

Ensemble Method:

Proposed Ensemble model Architecture is presented in Figure 2. To perform image classification concatenation utilizing three deep learning models, it is essential that the input dimensions of each model be uniform and measure 224 × 224 pixels. The original VGG-16 model had convolutional layers that were enhanced with ReLU activation, max-pooling, and batch normalization capabilities. The second model, DenseNet-121, may include convolutional and dense layers together with dropout for the goal of regularization. This model is specifically developed to incorporate a wide array of varied qualities. The third model, EfficientNet-B2, is likely to have a higher number of convolutional layers with batch normalization, while still accepting inputs of 224x224 pixels. Once the final layer representations of each model have been defined, a cohesive feature vector is created by combining them along a new axis. After combining and compressing into a single vector, this result is categorized using a common dense layer. By introducing dropouts before the thick layer, the model's capacity to generalize is improved and the occurrence of overfitting is avoided. This concatenated architecture maximizes the diversity of variables recorded by various models while keeping a consistent input size, resulting in an overall improvement in the performance of picture categorization. Precise tuning of hyperparameters and systematic experimentation are crucial for getting optimal optimization results.

VGG-16:

VGG-16 [22] is a 16-layer deep neural network that was submitted during the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). ILSVRC was a competition that assessed techniques to classify image at a large-scale. The image put at first stack of two convolution layers for the small receptive 3 x 3 size, using ReLU activations. These two layers consist of 64 filters. The convolutional stride is set at 1 pixel, and 1 pixel for padding. The configuration reserves the spatial resolution, and output activation map size is the similar as the input image dimensions. Activation maps are then put spatial max-pooling over a 2x2 pixel window using a stride of 2-pixels. So, the activations size at the end of the first stack is 112 x 112 x 64.

DenseNet-121:

DenseNets architectures resolve the problem of modifying the standard convolutional neural network and simplify the connectivity pattern among layers. Every layer is directly connected with each other layer in a DenseNet architecture. For 'M' layers, there are M(M+1)/2 direct connections. DenseNet components are named as connectivity, DenseBlocks, growth rate and bottleneck layers. DenseNet has two main features that make it significant compared to other CNN models. Firstly, it has a dense block, where every layer is connected to each other layer in a feedforward manner. Secondly, it applies bottleneck layers that are used to reduce parameters without reducing the features learned by the model [23]. DenseNet-121 architecture is presented in Figure 1(a).

EfficientNet-B2:

EfficientNet is a mobile-size baseline pure convolutional neural model that presents a novel scaling technique that consistently scales every dimension of resolution with a simple even efficient compound coefficient.

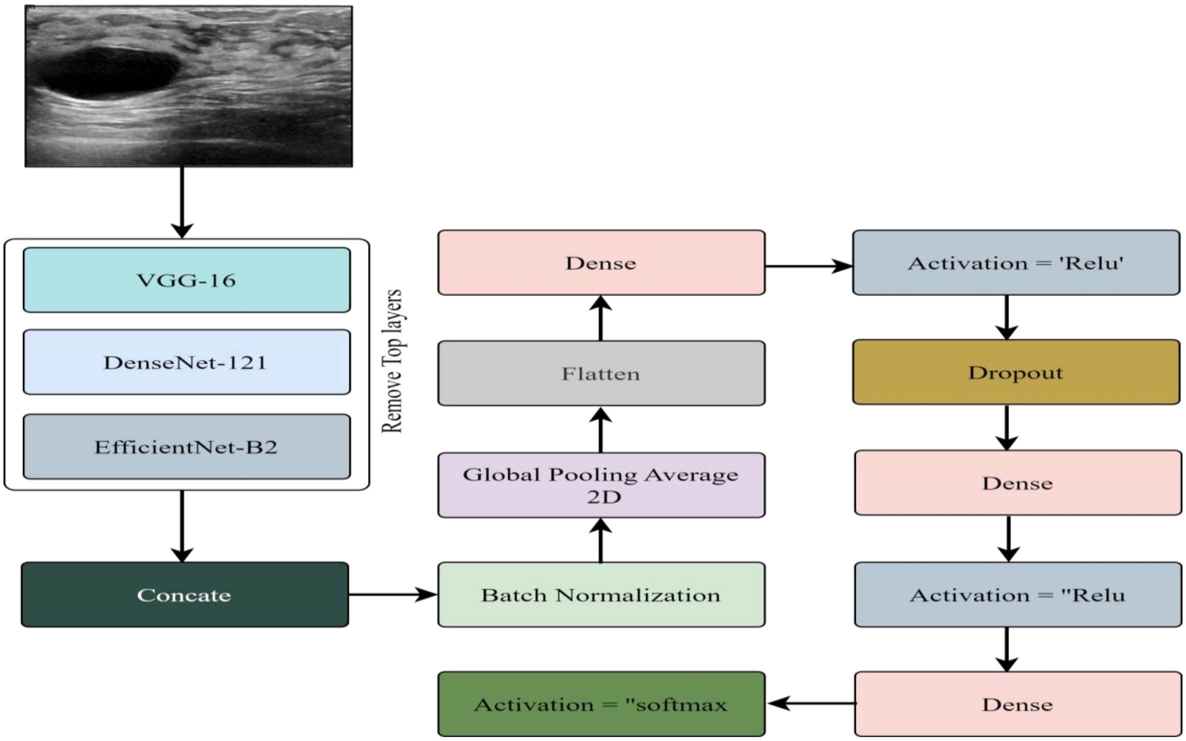


Figure 2. Proposed Ensemble Model Architecture.

This model is designed a standardized CNN expansion technique [24]. This approach can balance the depth, resolution, and width to optimize the accuracy and efficiency of the network. Moreover, the EfficientNetB2 network feature is inserted into two parallel channel and position attention modules to make new features. The self-attention technique is used in position attention module to capture the spatial dependence for the feature map among locations. Furthermore, it may select the aggregate and update the feature at every position with a weighted sum for the features. The channel attention module is used as a self-attention method to emphasize the channel inter-dependence among each channel map [25]. DenseNet-121 architecture is presented in Figure 1(b).

Results and Discussion:

Using a wide variety of cutting-edge deep learning strategies, this research endeavor conducted an exhaustive investigation into the classification of breast cancer. The main goals of this paper are to create a new deep ensemble model and compare its performance to well-known methods like VGG-16, ResNet-50, CNN, and MobileNet-V2. The item is studied in detail to ascertain both its advantages and disadvantages. During a complete assessment, the performance of the model is evaluated by analyzing a wide range of metrics, including accuracy, F1 score, recall, precision, area under the curve (AUC), and specificity. To make a significant addition to the area of medical image analysis, the fundamental purpose of this study is to identify and investigate Breast abnormalities. By doing so, the study hopes to accomplish its primary objective. In clinical practice, it is necessary to identify renal problems in a timely and correct manner. There is a possibility that the employment of deep learning technology might lead to an improvement in the accuracy of the diagnosis of cancer.

To test how well and how useful the proposed model is at classifying breast diseases, this study used an experimental method that relied on carefully choosing which software tools to use and how the hardware was built. The processing power was increased by using an NVIDIA GeForce RTX 3080 graphics card, 32 GB of RAM. To developing and improving our proposed model, we made use of the well-known deep learning frameworks known as TensorFlow and PyTorch. To ensure that the development process on the Jupyter Notebook platform was carried out without any interruptions, Anaconda 3 was utilized. Because of its extensive library and well-known adaptability, Python 3.10 is the programming language that we have decided to use to develop our study.

Performance of cutting-edge methods:

In recent years, convolutional neural networks (CNNs) have become a crucial method for deep learning in many image analysis applications, such as the classification of medical images. The CNN model was utilized to analyze the given information and effectively detect complex patterns and characteristics in images of kidneys. Table 2 presents a visual representation of the advanced capabilities of deep learning applications. The VGG-16 approach yielded findings with an accuracy of 96.87%, a recall of 95.07%, and a specificity of 97.63%. The ResNet-50 technique yielded a f1 score of 93.05%, along with an accuracy of 95.48% and a recall of 92.83%. The CNN model attained an accuracy of 95.41%, a precision of 93.93%, a f1 score of 93.07%, and a specificity of 96.53%, as reported. The MobileNet-V2 demonstrated a specificity of 95.79% and a precision score of 92.08%. The EfficientNet-B2 model demonstrated a precision of 95.48% and a specificity of 96.54%. The MobileNet approach has the lowest performance, while the VGG-16 method has the highest performance. The visual representation of performance is illustrated in Figure 3. All deep models attained low recall rate and highest specificity rate.

Table 2. Performance of deep transfer learning.

Methods	Accuracy	Precision	Recall	F1 score	Specificity
VGG-16	96.87	95.27	95.07	95.17	97.63
ResNet-50	95.48	93.36	92.83	93.05	96.54
CNN	95.41	93.43	93.05	93.07	96.53
MobileNet-V2	94.51	92.08	91.69	91.83	95.79
DenseNet-121	96.31	94.34	94.07	94.18	97.23
EffificentNet-B2	95.48	93.36	92.83	93.05	96.54

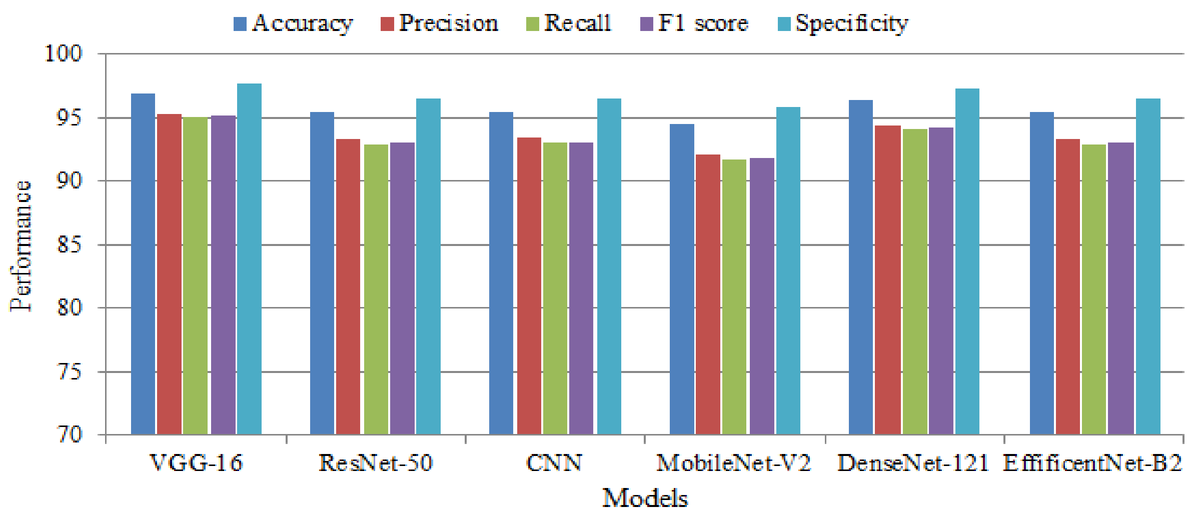


Fig. 3: Visual representation of deep transfer learning performance.

Performance of Proposed Ensemble method:

Table 4 shows the performance of the proposed ensemble method. Several different models are used in ensemble learning to get better generalization performance. Multilayer processing deep learning models are outperforming shallow or conventional classification models in terms of performance. Deep ensemble learning models combine the advantages of ensemble learning with deep learning models to produce a final model with better generalization performance. It has been highlighted how important it is to use simple, efficient, readily optimized, and thoroughly researched frameworks for group learning.

Table 4. Performance of proposed ensemble model.

Class	Accuracy	Precision	Recall	F1 score	Specificity
Benign	98.64	97.50	98.87	98.18	98.50
Malignant	99.74	99.70	99.40	99.55	99.83
Normal	98.54	98.09	96.61	97.34	99.27
Micro-Avg	98.95	98.43	98.29	98.36	99.20

A new deep neural network-based ensemble learning method has been proposed. Though it functions differently, the proposed approach is inspired in many ways by classification. The dataset is crucial for training and evaluating deep models. The dataset comprises a collection of medical images pertaining to breast cancer, specifically emphasizing four main categories: benign, malignant, and normal. The dataset used in the study has a diverse range of classes, which accurately represents the broad spectrum of breast-related cancer commonly observed in the field of imaging.

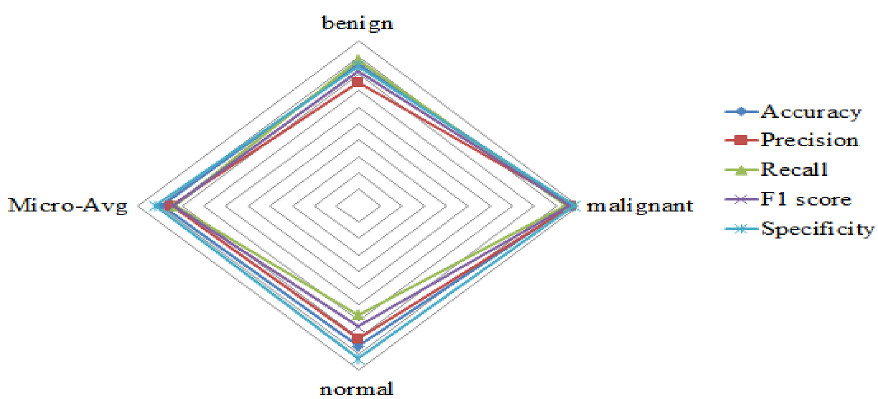


Fig. 4: Visual representation of proposed ensemble model using various metrics.

The proposed method achieved accuracy values of 98.64%, 99.68%, and 98.54% for the benign, malignant, and normal classifications, respectively. The proposed method achieved a micro-average accuracy of 98.95% and a specificity of 99.20%. The classification of malignant cancer has achieved an accuracy rate of 99.74% and a specificity rate of 99.83%. Figure 4 presents the visual explanation of the proposed method for three classes.

Cross Validation:

One statistical method utilized to assess the proficiency of ensemble models is known as cross-validation. It is frequently used in applied deep or machine learning to compare and select a model for a particular predictive modeling problem since it is straightforward to understand and implement and generates skill estimates that are generally less biased than those produced by other methods. Table 5 demonstrates the 10-fold results for breast cancer using ultrasound.

Table 5: 10-fold results for breast cancer

Methods	Accuracy	Precision	Recall	F1 score	Specificity
VGG-16	95.77±0.023	95.63±0.024	95.17±0.024	94.67±0.021	96.87±0.020
ResNet-50	94.97±0.021	94.26±0.015	93.98±0.021	93.23±0.029	95.73±0.013
CNN	94.87±0.042	93.40±0.052	94.02±0.083	94.10±0.032	96.31±0.018
MobileNet-V2	93.23±0.065	9212±0.065	92.12±0.075	92.32±0.023	95.14±0.018
DenseNet-121	96.91±0.023	96.21±0.021	95.23±0.013	95.13±0.048	96.92±0.032
EffificentNet-B2	96.12±0.018	94.36±0.018	95.12±0.019	95.02±0.032	97.81±0.017
Proposed	98.92±0.013	97.68±0.011	98.46±0.014	97.33±0.011	99.11±0.010

Figure 5 depict the precision and reduction in error of the proposed method when utilizing ultrasound images with sophisticated augmentation techniques. We attained a training loss of 0.011 and a validation loss of 0.018.

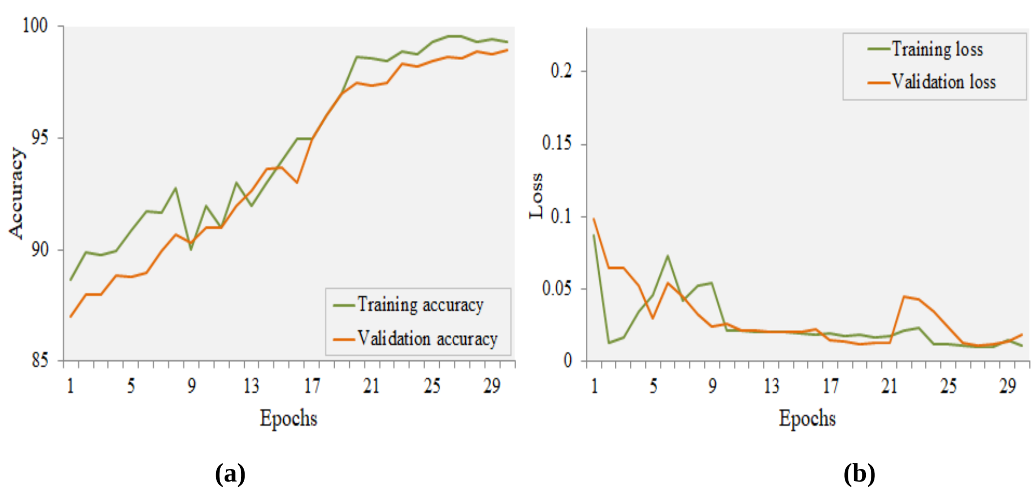


Figure 5. (a) Training and validation accuracy**, (b)** Training and validation loss

The classifier's efficiency is displayed via a specific table known as the confusion matrix. In machine learning, a confusion matrix is the usual name for an error matrix. The positivity or negativity of an image region is defined by the data type. Furthermore, the indicated outcome's determination can be correct (true) or wrong (false). Consequently, the option will be categorized as either a true positive (TP), a false negative (FN), a false positive (FP), or a true negative (TN). The diagonal of the confusion matrix shows the correct answer. Figure 6 shows a confusion matrix for three classes.

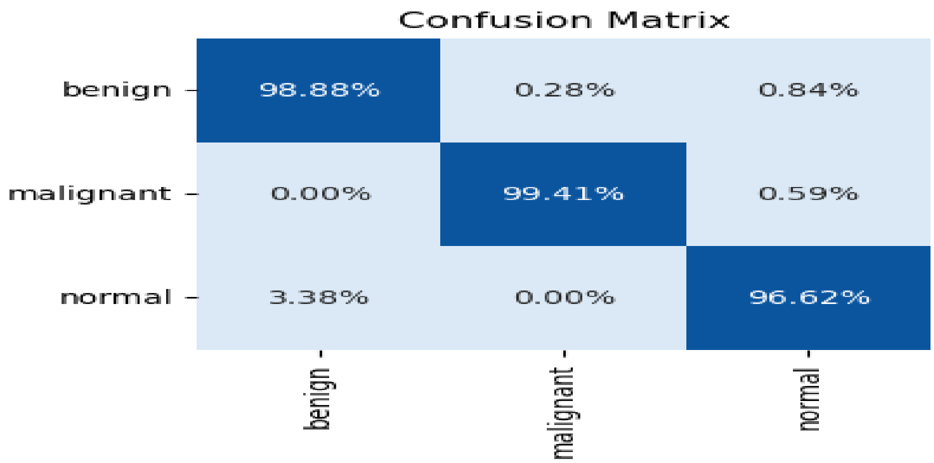


Fig. 6: Confusion matrix results.

Conclusion:

Worldwide, breast cancer is recognized as a prominent factor contributing to mortality among women aged 20 to 59. Timely identification and intervention can reduce the likelihood of adverse outcomes associated with breast cancer by facilitating patients' access to appropriate medical attention. The main emphasis of this research is on issues related to the interpretation of medical images for the diagnosis and categorization of breast cancer. It uses ultrasound scans and advanced augmentation techniques, to be more precise. 4,796 medical images were examined and classified as benign, malignant, or normal as part of the analysis. A flattened layer, max-pooling, and dropout layers are features of the proposed method that were described in depth. Six popular deep learning architectures were created, including VGG-16, CNN, ResNet-50, MobileNet-V2, DenseNet-121, and EfficientNet-B2. Compared to other models, the proposed method performed exceptionally well, taking less training time per unit of epochs to achieve a 99.74% accuracy rate. This is a significant breakthrough in the field of medical imaging concerning the detection and classification of breast diseases.

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