

An Integrated Deep Learning Framework for Automated Breast Cancer Identification

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Abstract: Breast cancer is a significant disease burden in the world and corrects and timely classification is essential to improve patient outcome and treatment strategies. Current diagnostic methods are generally subjective, and leave room for subjectivity and delays in treatment. For this purpose, we used the BRACS dataset which had 1000 images of two classes, Benign and Malignant. Applying augmentation techniques, we were able to get 6520 images, resized to 227x227x3. The models used in this work for classification of breast cancer are the VGG19 model with accuracy of 96.7% and the MobileNetV2 model with accuracy of 91%. This is true for VGG19 which had the best performance among all models. The results of the study underscore the value of deep learning and the use of augmented datasets in breast cancer classification to enable accurate detection and decision making in automated diagnostic systems and improve patient care.

Keywords: Breast Cancer; Benign; Malignant; Bio Informatics; Artificial Intelligence; Deep Learning; CNNs; VGG19; MobileNet V2

1. Introduction

Breast cancer is a complex disorder that is more common in women, resulting from an imbalance between the growth and death of its cells. If not treated, it may cause tumor formation and infiltrate surrounding tissues which may eventually spread to other parts of the body. Early detection and early intervention is important for good management and prevention of progression [1]. Breast cancer occurs in the tissue of the breast and presents with symptoms such as lumps, changes in the size of the breast or changes to the skin. The disease is the result of abnormal growth of cancerous breast cells that make tumors. It can invade the body's tissues and spread to other areas of the body (metastasis) in some cases [2]. In fact, breast cancer is the second most common cause of cancer deaths in women worldwide. The complexity of the diseases not only makes diagnosis difficult but also because of the varying clinical presentations. Manual diagnosis, which relies heavily on skilled medical imaging processing and interpretation of medical images like mammograms, ultrasound and MRI images, is time-consuming and requires experience to make accurate diagnoses [3].

The use of medical imaging, like mammography, ultrasound and MRI, is important in the identification and classification of breast cancer. These modalities provide a high level of information about breast tissue that can help to identify suspicious areas. However, the proper interpretation and classification may be challenging and only the radiologists can rely on visual clues. Diagnoses may be inaccurate and

inconsistent due to inter-observer variability and human error [4]. Figure 1 shows the incidence rate and mortality rates for the different types of cancers in 2023, with breast cancer having the highest rate among females [5]. Breast cancer incidence statistics by country, worldwide are presented in figure 2, which gives ASR (age-standardized rates) as a summary indicator to adjust for differences in the age structure and its effect on cancer incidence rates [6].

	Common Types of Cancer	Estimated New Cases 2023	Estimated Deaths 2023
1.	Breast Cancer (Female)	297,790	43,170
2.	Prostate Cancer	288,300	34,700
3.	Lung and Bronchus Cancer	238,340	127,070
4.	Colorectal Cancer	153,020	52,550
5.	Melanoma of the Skin	97,610	7,990
6.	Bladder Cancer	82,290	16,710
7.	Kidney and Renal Pelvis Cancer	81,800	14,890
8.	Non-Hodgkin Lymphoma	80,550	20,180
9.	Uterine Cancer	66,200	13,030
10.	Pancreatic Cancer	64,050	50,550

Figure 1. Worldwide Cancer estimated Incidence and death rate of various types

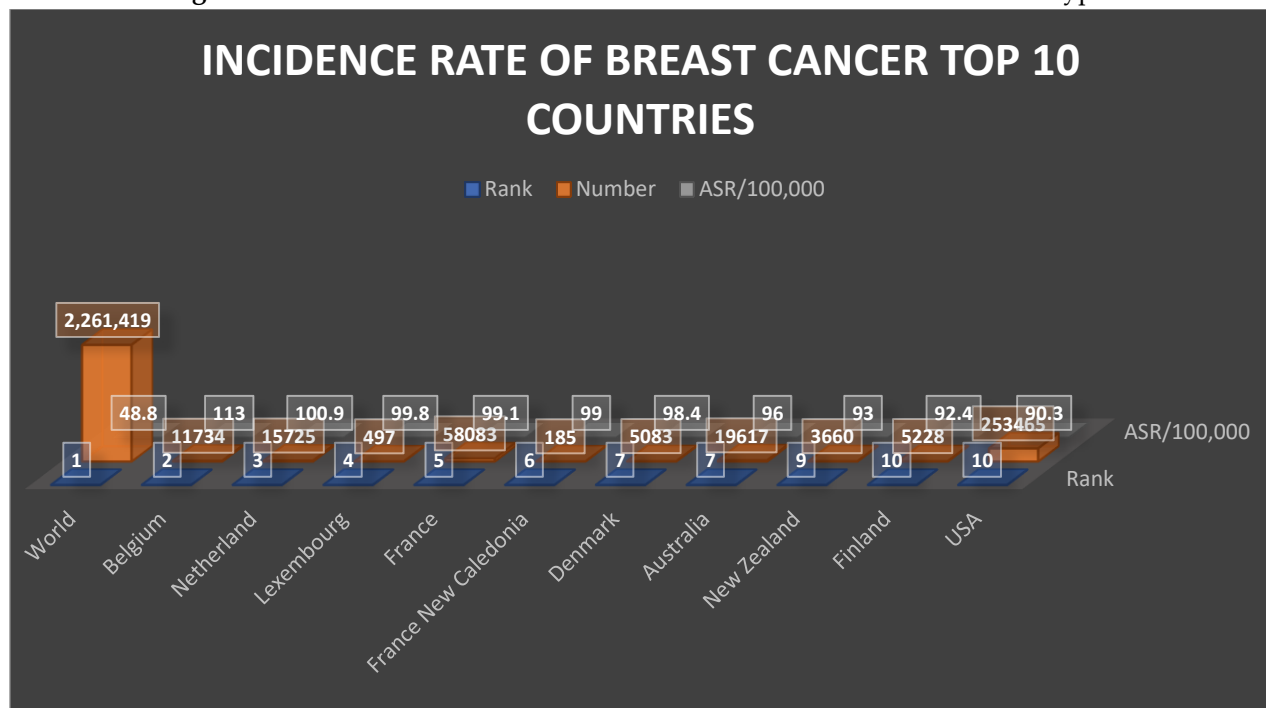


Figure 2. Worldwide Statistics of Breast Cancer 2022

In the field of medical imaging, deep learning, a branch of AI, has been used to overcome some barriers, such as the classification of breast cancer. Deep learning is a method with great achievement in numerous fields, including computer vision and natural language processing, and designed to automatically capture hierarchical representations from complex data [7]. These approaches use deep neural networks to improve accuracy, decrease inter-observer variability and speed up results for breast cancer classification. The applications of deep learning algorithms in different domains indicate that it could be applied in medical imaging analysis that would lead to quicker and accurate diagnosis [8][9].

As computing power, massive data sets and deep learning frameworks improve, deep learning can be used to analyze medical images, particularly for a breast cancer diagnosis, classification, and prognosis. The performances of these models are similar or better than the traditional models and improve the patient's health care [10]. Also, in the field of biomedicine, machine learning is used to solve problems related to breast cancer, making changes to the diagnostic process and extracting knowledge from the data, to change the way breast cancer is diagnosed. But there are still a number of hurdles, such as having access to large, diverse datasets, model interpretability, generalizability and embedding the models into clinical workflows [11].

2. Literature Review

The study suggests that the use of histological images (HIs) for automated diagnosis of breast cancer, with a training set of 7,909 RGB images with four different magnifications for both benign and malignant tumors. The set includes 5,053 training photos, 1,263 validation photos and 1,593 testing photos. The study uses improved capsule network, with Res2Net block and four extra convolutional layers, which are used to obtain multi-scale features. The proposed technique [12] involves reducing the number of parameters using Res2Net blocks and small convolutional kernel. Twenty-two thousand, twenty-five lymph node images are used for testing and training and 57, four hundred and fifty-eight unlabelled images are used for performance evaluation. It emphasizes the automation of detecting the metastases in lymph nodes with a hybrid classification method based on CNN. Two pretrained models (Resnet50, VGG16) and two fully trained CNN's (Mobile-net, Google net) are utilized for transfer learning and complete training [13]. In this research, CNN classifiers (ResNet50, VGG16, AlexNet) for breast cancer diagnosis using mammography images were investigated in three classes (benign, malignant and normal). Images were obtained from a mini-DDSM dataset, and due to its small size it was expanded using data augmentation techniques such as rotation and zooming. An effective model was achieved by implementing a validation ratio of 90:10 to evaluate the model [14]. This solution can be adapted to treat any breast cancer and combines histology and ultrasound images for computer aided detection and classification of breast cancer. The method is specifically designed for early identification, and is based on transfer learning between datasets A, B, C, and a variant A2. A CNN-AlexNet based model, specifically customized for the study, is trained with dataset parameters, and it involves ultrasonic imaging and histopathology to deliver an extensive analysis [15].

The purpose of this study was to evaluate the ability of deep learning classification to diagnose Kawasaki Disease (KD) and other acute febrile diseases based on coronary artery images. VGG19, Xception, ResNet50, ResNext50, SE-ResNet50 and SE-ResNext50 were the networks used to be trained and compared. Overall, SE-ResNext50 showed better accuracy, specificity, and precision. The study used a 10-fold cross validation approach which led to 10 different outcomes. A total of 14 or 15 images in the test set were used in each subgroup, and a total of 182 or 183 images were used for training in each subgroup [16]. The Modified Entropy Whale Optimization Algorithm (MEWOA) is suggested to extract the deep features and fuse them for classification. This method is simulation using MobilenetV2 and Nasnet Mobile model. The features are extracted and then optimized using MEWOA for the combined attributes. Then, the optimized deep features are used with the machine learning classifiers for the classification of breast cancer images. Three publicly available datasets, INbreast, MIAS and CBIS-DDSM [17] are used for the study. The authors used a small dataset of approximately 2620 mammography images obtained from the CBIS-DDSM. They used Deep Convolutional Neural Network (CNN) for segmentation and classification of different breast abnormalities like calcifications, masses, asymmetry and carcinomas. They pre-trained a ResNet50 model on their data and then trained a new deep learning model to refine the model, which they compare to ResNet50, but uses a 3x3 filter for spatial convolution [18]. In this work, two novel methods, ResNet50 and VGG-16 are fine tuned for two classes accurate and efficient classification. Transfer learning and data augmentation techniques are used to deal with the scarcity of labelled data. To further improve precision, the last fully connected layer is replaced by a support vector machine (SVM) encoder. The effectiveness of

the models is validated by using K-fold cross-validation technique. The proposed methodologies are trained and tested on three mammographic datasets: breast imaging subset of DDSM, DDSM and mammographic visualization society dataset [19].

The study uses ResNet50 and VGG-16 methodologies which are modified, adapted and fine-tuned to discriminate between two classes with accuracy. The support vector machine (SVM) encoder is developed to improve accuracy by replacing the previous entirely connected layer. The effectiveness of the model is verified using careful K-fold cross-validations. The methods are taught and tested with three mammographic image databases: the curated breast imaging subset of DDSM, the digital database for screening mammography (DDSM), and the mammographic image analysis society database [20]. The breast cancer images were subjected to image enhancement techniques such as CLAHE filtering, background removal, Wiener filtering and image restoration. Processed images were then fed into GoogleNet and AlexNet convolutional neural networks. Both RMSprop and SGDM optimizers were implemented at various learning rates (0.01, 0.001, and 0.0001) during the optimization process. To recognize breast cancer, PSO-MLP and ACO-MLP model was trained using the statistical features extracted from pre-processed images [21]. Another innovative approach combined a CNN and a BiGRU to model gene expression data, which is challenging due to minor example size and high dimensional features. The DCGN method successfully combined the performance of both neural networks as compared to seven other cancer subtype classification algorithms for two breast and bladder cancer gene appearance datasets [22].

Table 1. Limitations and Findings of the related work done in the domain

Author Names and Year	Technique	Dataset	Limitations
(Z. Wan et al, 2021)[23]	DenseNet	PatchCamelyon Dataset	The researchers used a large dataset consisting of over 22000 images for 2 classes but there is a class imbalance problem, and no technique was applied to entertain the issue.
(R. K. Samala et al, 2020)[24]	CNN Random Forest	DBT Dataset	Although the authors were able to develop a novel methodology, but the image dataset was limited to 307 images and no image augmentation was considered.
(W. M. Salama et al, 2020)[25]	ResNet50 VGG16	DDSM Dataset	The authors were able to produce good accuracy from the applied models and created a custom dataset. They used a very limited number of images per dataset that were 322, 564 and 330.
(S.Mohapatra et al, 2020)[26]	AlexNet VGG16 VGG19	Mini-DDSM	The research used data augmentation to increase number of images, but the train-test split ratio was kept 90:10 where only 10 percent of data was used for validation which is not sufficient and produced a maximum accuracy of 65%.
(F. Wang et al, 2020) [27]	3D U-Net	Automated Breast Ultrasound (ABUS) Dataset	The researchers have used a very limited dataset consists of a little over 300 images while the overall produced accuracy is 84% while is also not significant.
(S.Vedantham et al, 2013) [28]	Hybrid Machine Learning	Self-collected mammography images	The authors attempted to develop a state-of-the-art system, but the image dataset was limited to 307 images and no image augmentation was considered.

The study acknowledges that the proposed topic lacks novelty due to extensive existing research in various repositories. Finding a research gap is hard because each time, researchers have been tackling the challenge through different assignments, such as by using machine learning or deep learning in breast cancer classification. Some of the biggest drawbacks of the machine learning projects are the use of the older Wisconsin Breast Cancer Dataset, and the fact that there are no implementations of new algorithms or hybrid Deep-Machine approaches utilized. A number of studies are based on a single dataset, and have not included methods to be extended to other relevant datasets for comprehensive analysis. Generally used in Deep Learning, the "BreakHis" and "DDSM" datasets are frequently referenced in the literature, but have small numbers of images and classes, and are only used for binary classification. Many popular architectures, such as VGG16 and ResNet50, prevail and only a few attempts are made with newer CNN architectures. Besides, current works tend to be focused on the creation of good models, but neglect to suggest systems for practical usage in real medical centres or hospitals.

3. Proposed Methodology

The system proposed is based on Google Colab, which is a handy tool for creating deep learning and machine learning models deprived of particular ironware needs. The methodology is based on the "BRACS" dataset which is a diverse and independent binary class dataset. The Breast Carcinoma Subtyping (BRACS) data consists of labelled, annotated Hematoxylin & Eosin (H&E)-stained images from the BRACS website [29]. Over 1,000 images of regions of interest (ROIs) were extracted from Whole Slide Images (WSIs), which were then classified by board-certified pathologists into groups of benign and malignant lesions and each WSI was classified along with its associated ROIs. Figure 4 shows a methodology diagram, which indicates each step taken in the development of the approach.

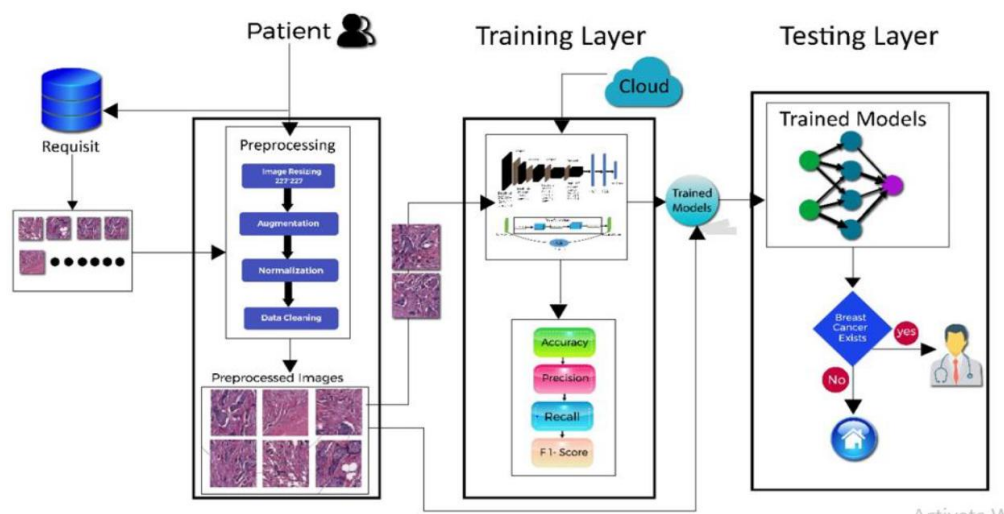


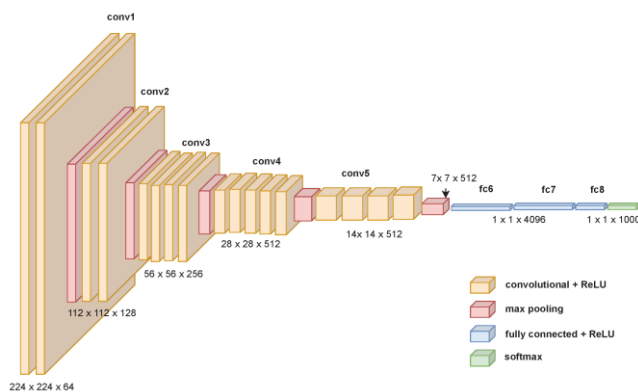
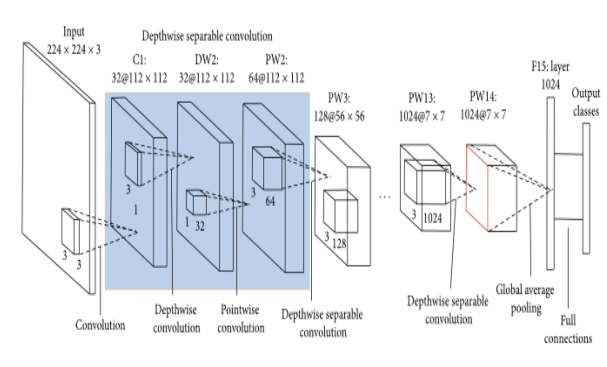
Figure 3. Proposed Model for Breast Cancer Classification.

Initially the data had 1000 images, which were divided into two classes: Benign and Malignant. But because of the small dataset and the tiny size of the original images (50 px), the task of training was challenging. To overcome these drawbacks, some significant pre-processed steps were done to give high quality of data for the purpose of accuracy improvement. The first step was to convert the data from a .DICOM format to a .PNG format. Using an online image convert it was then sorted by each class. This conversion was followed by the need to get more image samples - some dataset augmentation was done. To make the images more augmenting, horizontal and vertical flips, zooming in, resizing, rotation and affine transformations were performed. The results of such operations are reported in Table 2, which shows the number of images, their size and effect of augmentation per class. This table shows the significant enhancements made to the dataset in size and diversity that sidestepped the restrictions of the original dataset.

Table 2. No of images per class before and after augmentation

Class	Original images		After Augmentation	
	No of Images	Size	No of Images	Size
Benign	500	50px	3260	227px
Malignant	500	50px	3260	227px

The dataset was then expanded and normalized to obtain the same pixel ratios and colors. The data cleaning process was then used to exclude poor photos from the benchmark set. Then, a splitting of the train test set was done to divide the images into a 70-30 ratio (70% training set and 30% validation set). The same dataset and classes were used to train and validate both VGG19 and MobileNetV2 and the split ratio between train and test was similar in both models. VGG19 is a deep CNN architecture developed by the Visual Geometry Group (VGG) at the University of Oxford, which features 19 layers and a uniform structure with 3x3 filters and max pooling layers. It is very good at learning hierarchical representations of image features, but requires a lot of computational resources because of its depth. The architecture of VGG19 is described in figure 5 below[30] having 16 convolutional layers and 3 fully connected layers.

**Figure 4.** VGG19 Model Architecture [30]**Figure 5.** MobileNetV2 Architecture [36]

In figure 5 [31] a detailed breakdown of the MobileNetV2 architecture is provided, including the architecture's components, filters and layers. MobileNetV2 is a specialized convolutional neural network (CNN) architecture that is enhanced for image cataloguing on mobile and embedded devices. It brings novel concepts such as the depth-wise divisible difficulties, upturned remainders, lined blockages, expansion layers and squash and excitation modules. This design is a fine balance between model size, computational complexity and classification accuracy. Notably, MobileNetV2 achieves significant representation together with being efficient in computation, important for resource-constrained devices. It has become popular for real-time image classification on different platforms, such as mobile and embedded platforms. The metrics used for the model's presentation is presented in Table 3.

Table 3. Performance evaluation metrics and their equations.

Performance Evaluation Metric	Description	Equation
Accuracy	This is the overall meticulousness of the model's predictions, which is the proportion of instances that are correctly predicted (both positive and negative) to the amount of all instances.	$Accuracy = \frac{TP + TN}{FP + FN}$
Precision	Precision is a measure of how accurate positive predictions are what proportion of the predictions are correct so it trials the ratio of true positive forecasts to all positive forecasts. It shows the	$Precision = \frac{TP}{TP + FP}$

Recall	effectiveness of the model to achieve its desired false-positive rate, while securing a high true-positive rate.	
	Recall assesses the accuracy of positive guesses by manipulative the relation of correctly foreseen positive cases to all actual positive instances. It emphases on the model's capacity to identify positive instances, mitigating false negatives.	$Sensitivity = \frac{TP}{TP + FN}$
F1-Score	The F1 score is the combination of the precision and the recall. This will give a stable evaluation of the classification model, which is especially valuable in cases of imbalanced datasets, where the proportions of the classes vary greatly.	$F1 - Score = \frac{2TP}{2TP + FP + FN}$

4. Simulation and Results

This section elaborates on the complete simulation and deployment procedure of the proposed models, focusing on the designed method. The BRACS dataset, after augmentation, was employed and uploaded to Google Drive. Table 4 outlines the tuning parameters and image quantitative analysis applied for both models.

Table 4. Hyperparameters for both training and validation processes for VGG19 and MobileNetV2

	VGG19	MobileNetV2
Total Images	6520	6520
Training Set	4564	4564
Validation Set	1956	1956
Learning Rate	0.0001	0.0001
Optimizer	Adam	Adam
Image Size	227	224
Epoch	30	30
Batch Size	32	16

Figure 6 plots the development and verification accuracy and loss graph where the overall training and validation accuracy can be seen over a sequence of 30 epochs. Figure 7 shows the training accuracy as well as the overall validation accuracy. Figure 8-9 plots the confusion matrix of the training and validation process separately, here the true positive, true negative, false positive and false negative are stated. Figure 10-11 explains the presentation assessment metrics of the produced output and shows class wise accuracy for training and validation process separately.



Figure 6. Model Training and Validation Graph Accuracy and Loss Graph

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accuracy = 0.984375 ; loss = 0.052835
Validation: accuracy = 0.967773 ; loss = 0.103332
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Figure 7. VGG19 Training and Validation Accuracy

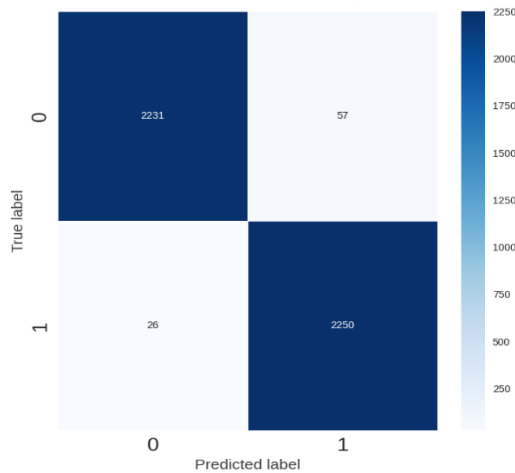


Figure 8. Confusion Matrix for training accuracy

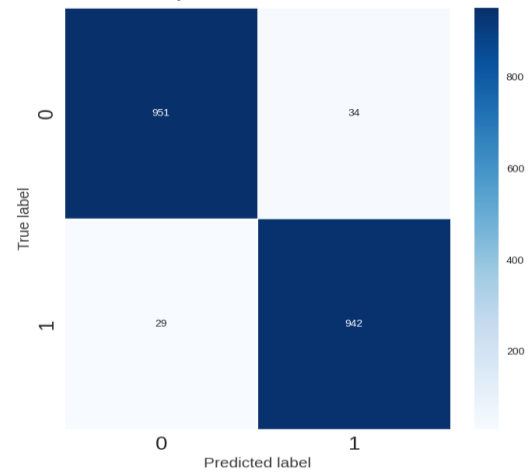


Figure 9. Confusion Matrix for Validation accuracy

	precision	recall	f1-score	support
0	0.99	0.98	0.98	2288
1	0.98	0.99	0.98	2276
accuracy			0.98	4564
macro avg	0.98	0.98	0.98	4564
weighted avg	0.98	0.98	0.98	4564

Figure 10. Class wise accuracy for Training process of VGG19

	precision	recall	f1-score	support
0	0.97	0.97	0.97	985
1	0.97	0.97	0.97	971
accuracy			0.97	1956
macro avg	0.97	0.97	0.97	1956
weighted avg	0.97	0.97	0.97	1956

Figure 11. Class wise accuracy for validation process of VGG19

Figure 13 plots the development and verification accuracy and loss graph where the overall training and verification accuracy can be seen over a sequence of 30 epochs. Figure 14 shows the training accuracy while too displays the overall validation accuracy. Figure 15-16 plots the confusion matrix of the training and validation process separately, here the true positive, true negative, false positive and false negative are stated. Figure 17-18 explains the presentation assessment metrics of the produced output and shows class wise accuracy for training and validation process separately.



Figure 12. Training and Validation Graphs for Accuracy and Loss

Training : accuracy = 0.943359 ; loss = 0.180375
 Validation : accuracy = 0.919922 ; loss = 0.225561

Figure 13. Validation Accuracy of MobileNetV2 Model

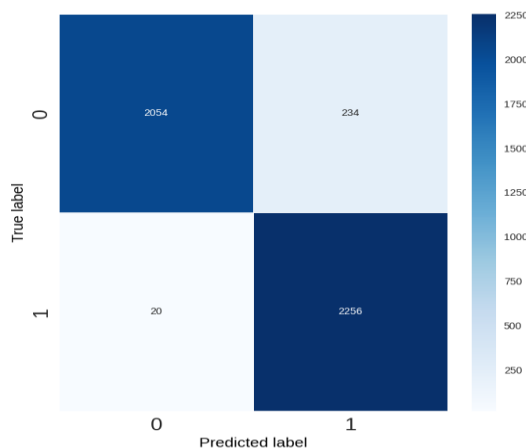


Figure 14. Confusion Matrix for Training process

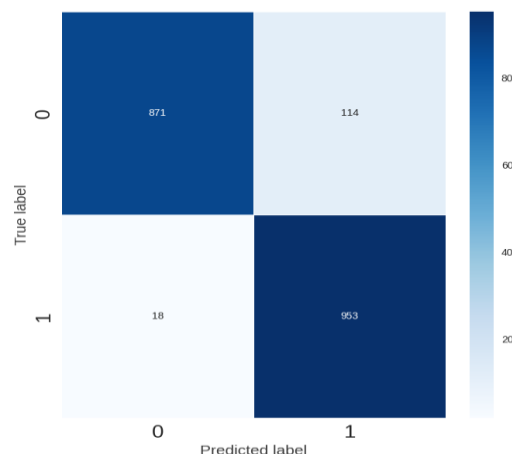


Figure 15. Confusion Matrix for Validation Process

	precision	recall	f1-score	support
0	0.99	0.90	0.94	2288
1	0.91	0.99	0.95	2276
accuracy			0.94	4564
macro avg	0.95	0.94	0.94	4564
weighted avg	0.95	0.94	0.94	4564

Figure 16. Class wise accuracy of MobileNetV2 Model

	precision	recall	f1-score	support
0	0.98	0.88	0.93	985
1	0.89	0.98	0.94	971
accuracy			0.93	1956
macro avg	0.94	0.93	0.93	1956
weighted avg	0.94	0.93	0.93	1956

Figure 17. Class Wise Validation accuracy of MobileNetV2 Model

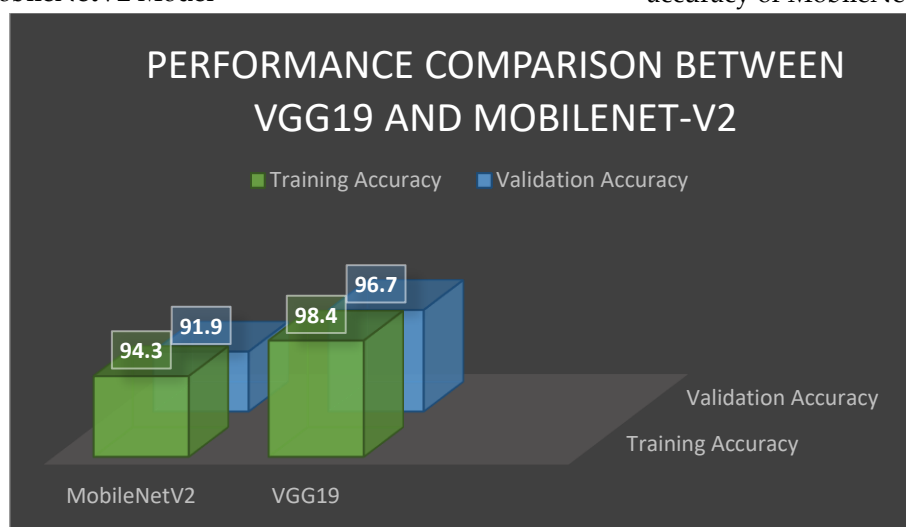


Figure 18. Comparative Evaluation of VGG19 and MobileNetV2

Table 4 states the relative analysis of the proposed exertion done with respect to accuracy where related work of few authors have been stated and compared in terms of accuracy. It can be observed that the proposed methodology had outperformed other researches and was able to produce the best results after all.

Table 4. Comparative Analysis of Prior Studies and Approaches

Author Name and Year	Technique	Dataset	Accuracy
(H. A. Khikani et al, 2019)[12]	Res2Net	BreakHis Dataset	95.6%
(J. Abdollahi, 2022)[13]	VGG16 VGG19 ResNet50 MobileNet V2	Camelyon16 dataset	94%
(M. H. M. Khan et al, 2021)[18]	CNN ResNet50	CBIS-DDSM	88%
(F. Wang et al, 2020)[27]	3D U-Net	Automated Breast Ultrasound (ABUS) Dataset	87.5%
(S. Mohapatra et al, 2020)[26]	VGG16 ResNet50	Mini-DDSM	65%
(L. Shen et al, 2019) [32]	Custom CNN ResNet50	CBIS-DDSM	91%
(M. A. Aslam and D. Cui, 2021)[33]	DenseNet	BreakHis	95.4%
Proposed Methodology	VGG19 MobileNetV2	BRACS	96.7% 91.9%

In this study, BRACS is used to classify the breast cancer into two classes: Benign and Malignant. The images were converted from DICOM to PNG and augmented with rotation, flipping, zooming, resizing and affine transformations and stored in two classes. VGG19 and MobileNetV2 were chosen to make a comparison between high classification performance and computational efficiency. VGG19 had an accuracy of around 96.7% on the validation set and MobileNetV2 had an accuracy of 91.9%. The data splitting procedure, however, needs to be clearly explained in the research, and augmenting only the train set, after the train-validation split, is required to avoid leakage. Also, numerical values for precision, recall, F1-score, ROC-AUC, and confusion-matrix should be given instead of just describing the metrics. Lastly, the study should state that a larger data set and high validation accuracy does not equate to clinical diagnostic performance and it will be necessary to test the data set independently at the patient level, validate the data set with external data sets and validate the data set by testing it in the clinical environment to demonstrate real world reliability.

5. Conclusion

Breast cancer poses a major international health concern, impacting heaps of women worldwide. Early diagnosis and appropriate categorization are crucial to better patient outcomes, higher survival rates and the best treatment for the patient. But the conventional diagnostic techniques based on subjective interpretation are time-consuming making diagnosis and treatment vary. Therefore, precise breast cancer classification using medical images, by helping health experts through reliable, efficient and automated systems is of critical need. To wrap up, application of deep learning models, in this case VGG19 and MobileNetV2, in the classification of breast cancer proved to be promising. VGG19 had a fantastic validation accuracy of 96.7% in the comparison study, outperforming the other models, including MobileNetV2.

With its deep architecture, VGG19 is able to accurately extract intricate features and patterns in breast cancer images, which is one of the reasons for its superior performance. The model learns the hierarchical

representations and has many layers of weights, which help to achieve high accuracy. MobileNetV2 achieves the same validation accuracy as VGG19 (91%), while also being more efficient in terms of computations and being smaller than VGG19, which can be advantageous for applications with restricted resources. The paper highlights the importance of choosing an appropriate model in deep learning, taking into account accuracy and computation efficiency, depending on the resources and deployment needs. The results obtained highlight the great latent of deep learning for the improvement of correctness in the classification of breast cancer, which can aid in the decision-making process of healthcare professionals. These advancements have significant implications for patient care, allowing healthcare professionals to make informed decisions and interventions at a quicker pace, help create personalized treatment strategies, and contribute to better patient outcomes.

Further research is required to explore why VGG19 works so well and how to fine-tune MobileNetV2 to obtain greater accuracy. In addition, efforts should be made to enhance the data set by recruiting additional patients and imaging modalities to increase model robustness and generalization.

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