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# A Binary Classification Model Based on VGG-16 for Breast Cancer Prediction

Research Article

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**Abstract:** Breast cancer is a great problem among women worldwide and constitutes nearly a quarter of all cancer cases. Early and precise detection is the first step toward saving lives and improving the living condition of patients. Even though there have been several developments in medical imaging and diagnostic technologies, the problems such as misdiagnoses, mistakes in expert interpretations, and lack of resources still remain. Traditional detection methods like mammography, ultrasound, and MRI rely heavily on expert interpretation and therefore may produce false positives and negatives, which is why the demand for automated, reliable, and alternative methods is rising. This article presents a study which leverages DL, particularly the VGG-16 model to improve the diagnosis of breast cancer from mammography images. The VGG-16 DL model that was initially trained was later fine-tuned to perform a two-class classification (Cancer and Non-Cancer) on a superior-quality dataset from Kaggle. The preprocessing steps made sure that the data was accurate and suitable, whereas, an 80-20 split of data was utilized in the training and testing phases to leave no stones unturned in the evaluation. The suggested architecture was capable of achieving quite an impressionable accuracy rate of 97.6% plus very excellent sensitivity, specificity, and precision, which were beyond most current methods for breast cancer classification. On the other hand, there are quite a handful of hurdles faced by AI deployment in healthcare, such as the quality of data, explanatory power of the model, and ethical aspects. Nonetheless, the paper focuses mainly on revealing the extraordinary power of DL to resolve the core issue of breast cancer at an extremely fundamental level.

**Keywords:** Deep learning, Transfer learning, VGG-16, Breast cancer

## 1. Introduction

Women are suffering from breast cancer, with over 2.3 million cases, as well as the death rate from cancer is 685,000 at the global level for a couple of years. When the breast cancer is detected at an early stage, it might be the key to improving survival rates, and with technological advancements, Artificial Intelligence (AI) has become a vital instrument in medical diagnostics. Classifying images as either "cancer" or " negative " has gained attention with the use of DL and VGG-16 models, which have been applied, providing a pioneer outcome in diagnosing and cataloguing of breast cancer [1]. Figure1 show bar graph indicating the expansion of the global breast cancer market between 2022 and 2032. The size of the market is in USD billion and is growing annually. In 2022, the market was worth $19.8 billion, and it is projected to be worth $49.2 billion by 2032. This expansion is occurring at a compound annual growth rate (CAGR) of 9.8%. The chart segments the market into various forms of therapies, such as targeted therapy, surgery, biologic therapy, hormonal therapy, radiation therapy, and chemotherapy. Each therapy is depicted in the bar by various colors. As time passes, the proportion of targeted therapy and biologic therapy appears to be higher, reflecting their growing relevance to treatment. The consistent growth in market size indicates that there is a driving force from improvement in cancer therapy and a rising number of patients. The lower section of the image identifies the most important details, including the forecasted value of the market for 2032 [2]. In this paper, the researcher tried its best to adopt a recognition model,

VGG-16, to diagnose the breast cancer with great accuracy so that analysis of the image could be done and resolve the problem of breast cancer [3]. There are multiple challenges faced by the re-searcher in analyzing the images so that the finest details could be retained through the usage of AI algorithms. The usage of VGG-16 with mammography, histopathological im-ages, and other diagnostic tools may classify cancer and negative with high precision and help to hasten more accurate diagnoses. Breast cancer results from uncontrolled multi-plication of cells within the breast tissue. Invasive ductal carcinoma is common, initiated within the milk ducts before it begins invading other tissue within the area [4]. Multiple causes can result in breast cancer: genetic makeup, age, hormonal imbalances, and even personal life. Although mammography is a routine screening procedure, the availability of newer, more advanced diagnostic imaging technologies including digital histopathology and ultrasound has improved detection capabilities [5]. Timely detection of breast cancer lowers mortality rates. The benign versus malignant nature of the tumor classifies the severity of the ailment and its treatment course accordingly [6]. However, manual classification is subjective and prone to error, thus AI-based approaches, like DL, have recently been integrated into diagnostic workflows to help radiologists to make precise pre-dictions [7]. Medical image detection is a basic aspect in disease to diagnose breast can-cer. These are mammography, ultrasound, MRI, and histopathology imaging of breast tissue to determine abnormalities. Usually, these images are analyzed manually, but with the ever-growing volume of medical data, automation through AI has become an imperative [8]. The prospect of automatically highlighting the presence of cancer from medical images to diagnose faster, more smoothly and with more accuracy, through DL models like VGG-16. Currently, the researcher wants to improve efficiency and efficacy by deploying image applications so that the optimum performance of image applications with pre-trained models be retained [9]. This method is claimed to outperform the conventional ones because it highly uses vast amounts of labeled image data, which has enhanced the detection of small and early-stage cancer [10]. Medical imaging, combined with DL, re-duces the burden on healthcare professionals yet results in better patient outcomes due to early intervention in a disease process [11]. In the current era, DL, particularly Convolutional Neural Networks (CNNs), has revolutionized the medical field. Nowadays, computers are performing tasks having better features to process the images, even the images are being inferred, the outcome is better with high precision, which will reduce the noise as well. VGG-16 is a very popular model being used in DL architectures improving the longitudinal resolution; it has 16 layers that enable the network to learn hierarchical features from an image [12]. The present researcher, regarding breast cancer, VGG-16 has been applied to mammograms, histopathological slides, and other imaging modalities to classify cancerous tissues. Its ability to learn complex features has been demonstrated with high potential for distinguishing malignant from benign lesions in cases of breast cancer [13]. In addition, DL, which fine-tunes pre-trained VGG-16 models, has significantly improved the accuracy of breast cancer classification tasks even when using relatively small datasets [14]. This development shows the DL in medical imaging to enable healthcare systems to make quicker and more reliable decisions and, therefore, improve patient prognosis [15]. This is because VGG-16 has been adopted as an equally important tool in the current diagnostic approach. It is a resource to the clinician in diagnosing breast cancer [16].

In summary, most of the women do not understand what breast cancer is, and doctors have the obligation to create awareness. But with more patients and fewer doctors, there is not enough time to create sufficient awareness. Models in this study have been presented that identify cancer faster with great accuracy. VGG-16 is one such model that has been used in a deep learning (DL) context to tackle breast cancer. The integration of DL in breast cancer research is essentially unfolding a whole new era that is changing the face of detection, diagnosis, and treatment by providing innovative solutions. Through AI capabilities, healthcare practitioners and researchers can, in a manner, collaborate to offer a care system that is more accurate, less time-consuming, and equally accessible to everyone. Nonetheless, to fully unlock the benefits of AI in healthcare, we must first over-come the technical, ethical, and operational hurdles that are bound to arise with the use of AI in medicine. This model is part of the continuing research that seeks to probe the conjunction of breast cancer and deeply analyze the issues and future prospects of the field. This paper aims to study the binary classification of Breast Cancer in detail. Introduction explains the reason behind using DL for an accurate diagnosis and thereby, the significance of the same. Through the lens of a literature review, one gets an understanding of different methods used, the variety of models implemented, and also the gaps and limitations in the field. The model that has been proposed here discusses the networks in detail and basically focuses on the superior performance of the VGG-16 model in classifying images into two categories. The simulation and results validate the proposed model's performance, achieving high accuracy and demonstrating its robustness. The conclusion summarizes the findings, emphasizing the model's potential for clinical applications and the future works.

## 2. Related Work

During the literature review, the authors identify the gaps in the literature clearly and puts forward a hybrid framework model as a solution. In order to justify this, the author has reviewed several studies to point out different perspectives of breast cancer classification and its associated issues. The authors in [17] investigated a number of machine learning classifiers, e.g. MLP, AdaBoostM1, Logit Boost, Bayes Net and J48 decision trees, for the purpose of breast cancer classification. The comparison between 10-fold and 5-fold cross-validation showed that 10-fold cross-validation was more effective in achieving the optimum model performance. They articulate their results that selecting suitable validation techniques is crucial for breast cancer diagnosis. Similarly, the authors in [18] have developed an autoencoder-based DL method for breast cancer histopathology images grading automatically. Their approach was nuclear atypia analysis, which is the main determinant of breast cancer grading severity. Incorporation of deep stacked multi-layer autoencoder ensembles enabled them to achieve very good results in recognizing different lesion types accurately, thus laying a foundation for automated histopathological grading. Moreover, DL has been successfully applied in other medical imaging scenarios besides breast cancer. The authors in [19] applied convolutional neural networks (CNNs) for the detection and classification of diabetic retinopathy. Their study was more focused on demonstrating how DL models such as VGG-16, VGG19, DenseNet121, and MobileNetV2 can be trained at multiple stages to achieve a very high classification accuracy for retinal diseases. The success of their method is a testament to the adaptability of CNN-based architectures to various healthcare fields. In the same way, the authors of [20] presented a CNN-based system for the classification of different stages of Alzheimer's disease. Their study was MobileNet based along with other pre-trained models. The research work has shown that DL can be of great use in the early diagnosis and monitoring of disease progression. The study's results which attained an accuracy percentage of 96.6 percent have demonstrated that CNN is useful not only in breast cancer medical image classification but also in other areas of research. There have been some other works on the classification of breast cancer as well. The researchers in [21] suggested a DL model for the multi-class classification of breast cancer. They utilized the hierarchical relations between cancer subtypes to regulate accuracy and robustness. Meanwhile, the authors in [22] proposed an auto body segmentation algorithm for the rapid generation of digitally reconstructed radiograph (DRR) images. In medical imaging processing, the use of the method for DL-based body segmentation yielded a significant boost in computational efficiency. The authors in [23] managed to correlate tissue texture and morphological characteristics with cancer grade, thus developing cancer grade algorithms. They significantly improved the accuracy of cancer grading through automation by infusing the model with deep knowledge of tissue. The authors in [24] executed the adaptive sparse support vector ma-chine (SSVM) for the classification of breast cancer and they also performed feature selection optimization to achieve the highest accuracy with the lowest computational complexity. The method was efficient for large-scale histopathological data processing. Be-sides, the authors in [25] introduced a method based on transfer learning for the classification of breast cancer in histopathological images and they showed that pre-trained models can facilitate higher classification accuracy when working with different magnification levels.

Furthermore, the authors in [26] have developed a DL setup that makes use of random patch aggregation and depth-wise convolutions as a means to reduce the computational demand of breast cancer classification. While the authors in [27] utilized transfer learning to gather deep knowledge features for the classification of mammography images, the authors in [28] built a CNN model specifically for histopathological image classification and the model achieved higher accuracy than other conventional methods. The authors in [29] re-searched the use of CNN models for breast cancer histology image classification and proved the capability of these models to identify cancer automatically. The authors in [30] suggested a deep convolutional neural network (DCNN) for the classification of medical images which highlights the diagnosis of diseases from different medical imaging techniques. Their method opened up the possibility of using CNN for handling complex medical image datasets to make a correct diagnosis.

Table 1. Limitations in the literature review

| **Ref.** | **Model Used** | **Accuracy** | **Use Classes** | **Dataset Type** | **Key Observations / Limitations** |
|---|---|---|---|---|---|
| [4] | CNN | 95.6% | 2 Classes | BreakHis Dataset | High accuracy for binary classification; limited to specific dataset. |
| [7] | CNN | 96.9% | 2 Classes | Histopathological Images | High accuracy, but specific datasets not detailed. |
| [8] | Pre-trained CNN | 94.0% | 2 Classes | Histopathology Dataset | Utilized pre-trained CNNs, with focus on feature extraction. |
| [9] | DL | 97.3% | 2 Classes | Histopathology Dataset | Ensemble approach achieved high accuracy; model complexity noted. |
| [12] | CNN | 88.8% | 2 Classes | ImageNet | Well-known architecture for image classification; not specific to breast cancer. |
| [14] | VGG-16 | 92.5% | 4 Classes | Mammography Images | Focus on mammography, accuracy is promising, but focused on specific images. |
| [28] | CNN | 94.0% | 2 Classes | Histopathological Images | Used CNN for classification, good accuracy but no further model details. |
| [21] | DL | 93.2% | 2 Classes | Histopathological Images | Multi-class classification with DL; no further accuracy clarification. |
| [29] | CNN | 96.0% | 2 Classes | Histopathology Dataset | Effective for histological image classification; no accuracy with specific datasets. |

Table 1 exhibits the most important models and their weaknesses from the literature, showing their accuracy, types of datasets, and main problems. The studies [17-20] offer additional perspectives to this discussion, highlighting the significant impact of DL in various sectors of medical imaging.

### 2.1. Limitations of the Literature Review

1. Methods such as Support Vector Machines with Recursive Feature Elimination (SVM-RFE) and convolutional deep neural networks (DNNs) demand significant computational power, making real-time processing challenging, particularly in resource-constrained environments [6], [13], [11].
2. Existing models exhibit lower classification accuracy, as reported in [4], [7], [8], [9], [14], [28].
3. Performance evaluation remains insufficient in several studies, lacking comprehensive validation across multiple datasets and evaluation metrics [4], [7], [8], [9], [14], [28].

### 2.2. Contribution of Proposed Model

1. The VGG-16 model was utilized and fine-tuned on a medical dataset for binary classification, achieving an accuracy of 97.6%, surpassing previous approaches.
2. To optimize performance for binary classification, the VGG-16 architecture was modified by adjusting specific layers, integrating Flatten and Dense layers, and incorporating a Sigmoid activation function in the output layer.
3. Model performance was further enhanced using nine confusion matrix metrics to maximize accuracy and minimize cancer detection errors.

## 3. Methodology

In Figure 1, the DL process applied to diagnose the breast cancer condition and data has been collected from Kaggle. There are 410 images divided into 2 folders “Cancer” and” Negative”. Each folder contains 205 images. First step, therefore, deals with getting the dataset, with information related to cases of breast cancer. Second step, preprocesses the images to feed into a DL model. It resizes all the images to 224x224 pixels so that their dimensions are standardized. It then changes the images to tensors, which the models understand, and then it normalizes image data, ensuring consistent brightness and color, by scaling with common values of mean and standard deviation. the data involved cleaning and normalizing the data, thus getting it ready for proper analyses. Third step, the processed data is Split into two parts: 80% for training and 20% for testing. Fourth and Fifth step, the reason behind is that training data will be used to train the DL model, whereas the testing data will be reserved to test the performance of this model. A DL model used in this pipeline is VGG-16, a strong CNN specially designed for the image classification tasks. Sixth and seventh step, the training phase feeds the training data into the VGG-16 model where the model learns patterns and relationships within the data. Post-training, there is a phase of performance measurement. In cases where performance was not up to the mark, the loop backs for further refining the process in training. Once the model achieves acceptable performance metrics (e.g., accuracy, precision, recall), it is finalized as the trained model. Eight step, final model is then subjected to an additional round of evaluation to ensure its reliability and effectiveness. If the model meets the desired standards, it is saved as the final model, ready for real-world deployment. Tools like Databricks are used in this process to streamline the workflow, from data handling to evaluation and finalization.

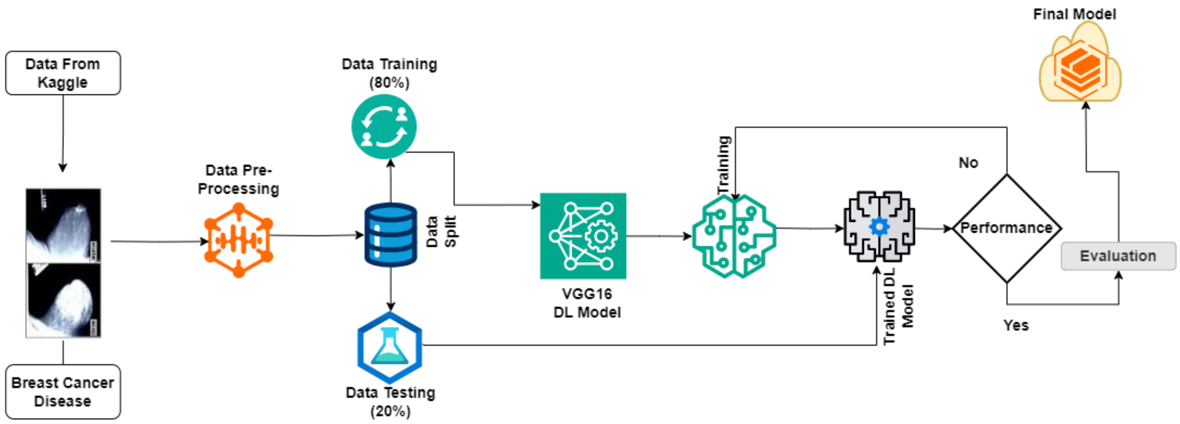
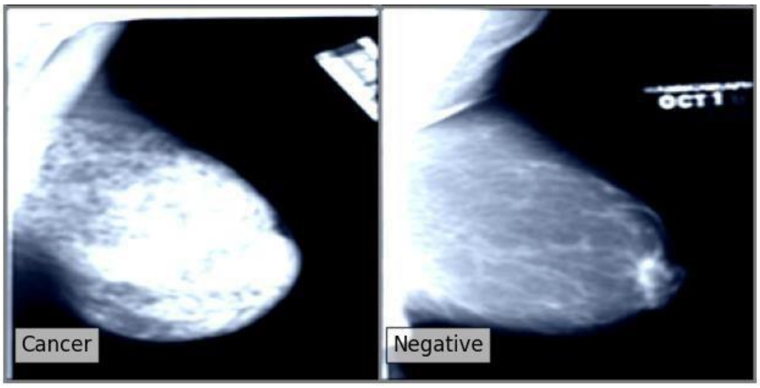



Figure 1. Proposed methodology design

### 3.1. Dataset

Kaggle dataset has two directories: "Negative" and "Cancer" [31]. Figure 2 shows sample images of cancer and negative.




(a) (b)

Figure 2. (a) for cancer and (b) for negative [31]

Table 2 shows a Kaggle dataset of 820 total images, with an equal distribution of cancerous (410) and noncancerous (410) images. The dataset is distributed between training (80%) and testing (20%) sets. During training, 328 cancer and 328 non-cancer images are utilized. During testing, 82 cancer and 82 non-cancer images are utilized for model performance evaluation.

Table 2. Breast Cancer Dataset form Kaggle

| | | | | | | |
|---|---|---|---|---|---|---|
| **Total Images** | 820 | **Cancer** | 410 | Training | 80% | 328 |
| | | | | Testing | 20% | 82 |
| | | **Negative** | 410 | Training | 80% | 328 |
| | | | | Testing | 20% | 82 |

### 3.2. Transfer Learning

TL improves diagnostic accuracy with the help of pretrained models on huge image repositories and finetuning them for a particular task like disease classification of X-rays, MRIs, or CT scans. Models of VGG are commonly used to detect diseases like pneumonia, tumors, or diabetic retinopathy. This technique greatly accelerates training and improves performance, especially when labeled medical data are limited and applies the VGG-16 TL model to classify medical images as "negative" or "cancer." Pretrained VGG-16 model (without top layers) will be utilized to extract features and add custom layers for classification. The model will be fine-tuned from the dataset to achieve better accuracy in detecting cancer.

#### 3.2.1. VGG-16 Architecture

Figure 3 depicts the architecture of the popular DL model VGG-16 in relation to tasks involved in image classification. VGG-16 is a simple yet consistent form of Convolutional Neural Network. It breaks the input image down step by step to understand its patterns and place it in relevant categories. It takes an input image of size 224×224×3, where the three values indicate the height, width, and number of color channels respectively. The model employs a Cascade of Convolutional Layers (blue boxes), each of which essentially acts as a filter sliding over the image to detect common patterns such as edges, textures, and shapes. These layers produce several feature maps, thus increasing the capacity of the network to identify intricate features. After each convolution operation, a function called ReLU or Rectified Linear Unit is applied which basically introduces non-linearity. It will allow the network to learn much more complex patterns than simple linear models are capable of. Max Pooling Layers (yellow) are used afterwards, which help to reduce the spatial dimensions of feature maps, for instance, from 224x224 to 112x112, etc. This greatly decreases the amount of computation and also directs the attention to the most crucial parts of the image.

In the process of image data going through a model, at one point, the spatial dimensions of the image are reduced to 7×7 pixels while the number of extracted features increases from 64 to 512. In other words, the network first learns to recognize very basic features like edges, then it gets to the level of identifying complex features such as shapes and objects. At the last stages, the features that have been extracted are combined into one very long vector and then fed through the Fully Connected Layers (green boxes). These layers integrate all the information to make a choice of what the image conveys. The last layer, the Softmax Layer (red box), provides a prediction in the form of probabilities of different classes, thus determining the category of the image [14].

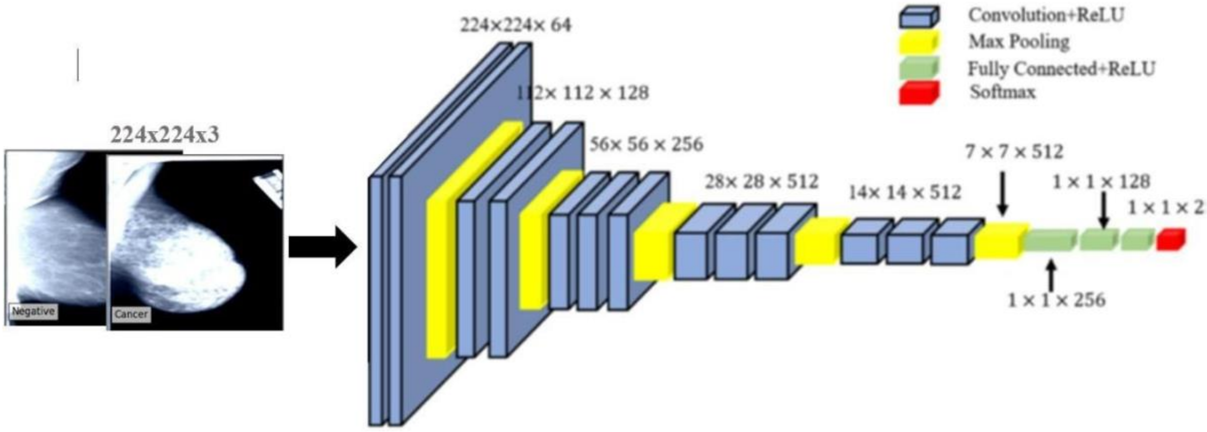



Figure 3. Proposed modified architecture of VGG16 [14]

## 4. Results and Discussion

Google Colab together with Python is utilized for simulation and analysis. The dataset is being trained with a batch size of 32, which means weights are optimized after each mini-batch. Over more than 15 epochs, Adam optimizer is engaged to achieve the efficient and adaptive updates of the model parameters. The learning rate of 0.0001 is applied in the model to make the convergence toward loss minimization smooth and stable.

The proposed method is able to divide Breast Cancer microscopic images into Cancer and Negative categories. The training parameters of the proposed model, such as the optimization algorithm, number of epochs, batch size, input image size and learning rate, are presented in Table 3.

Table 3. Training parameters of the proposed model

| Parameters | Value |
|---|---|
| Total Batch Size | 32 |
| No. of Epochs | 15 |
| Optimizer Algo | Adam |
| Size of Input Images | 224x224 |
| Learning Rate | 0.0001 |

### 4.1. Evaluation Metrics

Evaluation metrics to measure the performance of the proposed method are outlined in the given equations 1-9.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (1)$$

$$\text{Misclassification Rate} = \frac{FP+FN}{TP+TN+FP+FN} \times 100 \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100 \quad (3)$$

$$\text{Recall / Sensitivity} = \frac{TP}{TP+FN} \times 100 \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100 \quad (5)$$

$$\text{Negative Predictive Value} = \frac{TN}{TN+FN} \times 100 \quad (6)$$

$$\text{False Positive Rate} = \frac{FP}{FP+TN} \times 100 \quad (7)$$

$$\text{False Negative Rate} = \frac{FN}{FN+TP} \times 100 \quad (8)$$

$$\text{F1} - \text{Score} = 2 \times \frac{Precision * Recall}{Precision + Recall} \quad (9)$$

## 5. Confusion Matrix

Figure 4 shows the confusion matrix of the proposed model using the testing data set. In this study, the Cancer class is considered the positive class, and the Negative (Non-cancer) class is considered the negative class. From the results, the proposed model classified 79 cancer images as cancer (True Positives) and 81 non-cancer images as non-cancer (True Negatives). Moreover, the model incorrectly classified 1 non-cancer image as cancer (False Positive) and 3 cancer images as non-cancer (False Negative). It is evident that the proposed model can differentiate between cancerous and non-cancerous images with minimal misclassification, hence showing its effectiveness and reliability in breast cancer image classification.

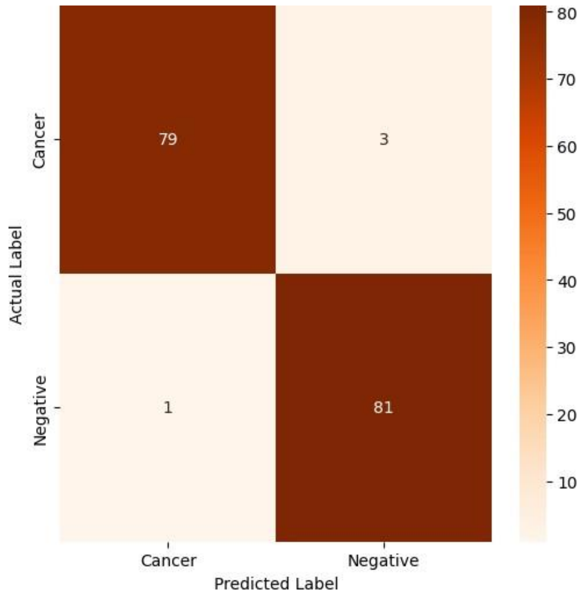



Figure 4. The proposed model confusion matrix during testing

Table 4. Proposed model evaluation matrix for the testing

| Sr. | Parameters | Results |
|---|---|---|
| 1 | Accuracy | 97.6% |
| 2 | Misclassification Rate | 2.4% |
| 3 | Specificity | 96.4% |
| 4 | Recall | 98.8% |
| 5 | Precision | 96.3% |
| 6 | Negative Prediction Value | 98.7% |
| 7 | False Positive Rate | 97.5% |
| 8 | False Negative Rate | 1.2% |
| 9 | F1-Score | 0.975 |

These measurements will tell us the extent to which a model is performing well at classifying data. An accuracy of 97.6% means that it is correct 97.6% of the time and the misclassification rate of 2.44% is the number of times it is incorrect. Specificity of 96.4% indicates how well it identifies negatives and recall of

98.8% means how many of the positives it correctly identifies. Precision of is the correctness of positive predictions, and Negative Predictive Value of 96.3% and 98.7% is the correctness of negative predictions. False Positive Rate of 97.5% negatives incorrectly classified as positive, and False Negative Rate of 1.2% is the positives missed by the model. F1-Score of 0.975 is the balance between precision and recall for an overall performance measure.

Figure 5 represents an ROC curve for performance analysis of a classification model where it plots the true positive rate versus the false positive rate at various settings of the thresholds. In such a graph, the X-axis is False Positive Ratio, which denotes the proportion of false positives while the Y-axis is TPR, which means the proportion of correctly predicted positive cases. The trade-off between sensitivity and specificity is given by the blue line in the graph. The curve hugs the topleft corner, and the Area Under the Curve (AUC) is 1.0. That is, this is a perfect classifier: it correctly classifies all positives and all negatives without a single error. This is an ideal model

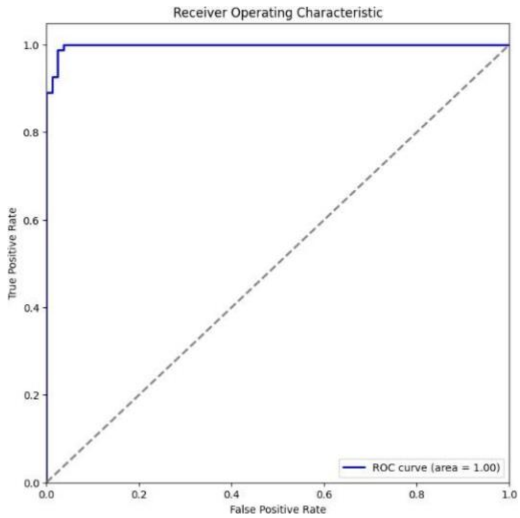



Figure 5. Proposed model ROC curve for breast cancer

The two plots in Figure 6 show how well the model works for both training and testing after a number of epochs. The left plot shows Training and Testing Loss, which is a measure of the error or difference between the actual and predicted values. At the beginning, both losses are high but then they fall very quickly with each epoch. The training loss just keeps going down and it almost hits zero, which means the model learns very well from the training data. On the other hand, the testing loss levels off and varies a bit, indicating that the model's ability to generalize to unseen data is limited after a certain point.

The right-hand graph plots Training and Testing Accuracy, showing how well the model predicts by calculating the percentage of correct predictions. The training accuracy shoots up rapidly and reaches 100% within a few iterations, hence performing very well on the training data. Testing accuracy increases very rapidly at first and then levels off to around 97.6%. This difference in training and testing accuracy suggests roughly overfitting where the model performs better on the training data than on the testing data. In summary, plotting suggests that even though the model is learning, it still overfits to some extent because testing loss is slowly moving and there is a minor accuracy gap. Some regularization technique or more data may be used to minimize overfitting.


Figure 6. Training and testing loss and accuracy for proposed model

Figure 7 presents two mammography images of a breast, likely detect Cancer. The two scans each bear the inscription "Cancer (✓)," which indicates they are positive for breast cancer. The light-colored white patches might represent unusual growths or tumors. The two scans assist physicians in early detection and diagnosis of breast cancer.

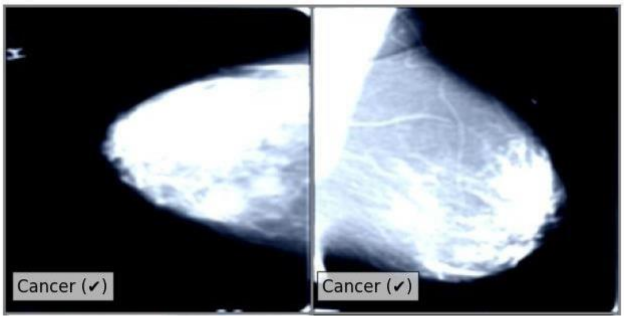



Figure 7. Testing sample for proposed model cancer prediction Model

Table 5. Comparison of proposed model with the state of the art

| Reference | Model Name | Accuracy | Misclassification |
|---|---|---|---|
| [4] | CNN | 95.6% | 4.4% |
| [7] | CNN | 96.9% | 3.1% |
| [8] | Pre-trained CNN | 94.0% | 6.0% |
| [9] | DL | 97.3% | 2.7% |
| [12] | CNN | 88.8% | 11.2% |
| [14] | VGG-16 | 92.5% | 7.5% |
| [28] | CNN | 94.0% | 6.0% |
| [21] | DL | 93.2% | 6.8% |
| [29] | CNN | 96.0% | 4.0% |
| **Proposed Model** | **DL Algorithm VGG-16** | **97.6%** | **2.4%** |

While both the proposed model and that of [14] use VGG-16, key modifications differentiate our approach. First, the proposed model is trained on a different dataset, which may contribute to improved generalization. Second, our data augmentation strategy incorporates additional transformations beyond those used in [14], enhancing robustness. Third, the optimization strategy in the proposed model differs, potentially using an improved loss function, adaptive learning rates, or enhanced transfer learning strategies. Lastly, adjustments in the fully connected layers and number of training epochs further explain the accuracy gain from 92.5% in [14] to 97.6% in our work

## 6. Conclusion

The paper highlight that DL, with the VGG-16 model, has a great potential in breast cancer diagnosis. The authors managed to outperform a number of different approaches in terms of accuracy, sensitivity, and precision by employing a pre-trained VGG16 model and making appropriate adjustments for binary classification. Their success also depended on having a good dataset from Kaggle, utilizing efficient data preprocessing, and implementing sound performance evaluation methods. The model was successful in identifying breast cancer images. Changes, however, still need to be made as a challenge remains from aspects such as data quality variation, high demand for computing power, and the necessity of validation in real-life situations. This article reaffirms the revolutionary impact of AI on the healthcare sector and highlights its capacity to raise diagnostic accuracy, facilitate early detection, and help limit misdiagnosis. The discoveries provide a basis for continued developments in AI-based medical imaging.

Future studies will mainly revolve around finding ways to make the model decisions more transparent and thus gain patient trust in AI-based diagnostics. On top of that, ethical issues, especially in relation to patients' data privacy and bias prevention, will remain a major point of discussion. To showcase the flexibility of the model, future research will also experiment with various clinical scenarios by utilizing healthcare facility datasets from different parts of the world, thereby ensuring wider acceptance and equitable health outcomes. Besides that, the data used for the training will be extended not only for binary classification but also to encompass the various subtypes of breast cancer, thus facilitating detection and classification at a refined level. Explainable AI (XAI) methods will be used to clarify how the model operates, thus building more trust for adoption in the clinic. Data augmentation techniques will be continually evaluated and applied as necessary, providing the model with more power and universal applicability. In the end, such enhancements are intended to bridge the gap between AI investigations & medical implementations in the real world, thereby unleashing the potential of cancer detection systems that are not only efficient but also scalable

# Declarations

## Author Contributions Statement

**Syed Muhammad Ali:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review and editing. **Naila Sammar Naz:** Conceptualization, Validation, Writing – review and editing, Visualization, Supervision. **Muhammad Saleem:** Conceptualization, Formal analysis, Investigation, Data curation, Writing – review and editing, Supervision. **Muhammad Mazhar Ali:** Methodology, Investigation, Data curation. **Muhammad Ahmed:** Software, Validation, Visualization. **Fahad Ahmed:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review and editing, Visualization. All authors have read and approved the final version of the manuscript.

## Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Data Availability Statement

The data and materials used in this study is publicly available at Kaggle repository https://www.kaggle.com/datasets/ahmedmohamedabdallah/breastcancer.

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