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# DENSENET-DRIVEN MULTI-LEVEL FEATURE REPRESENTATION FOR EARLY BREAST CANCER DIAGNOSIS IN MEDICAL IMAGING

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## ABSTRACT:

Treatment results and patient survival rates are greatly enhanced by early and accurate identification of breast cancer. Convolutional neural networks (CNNs), a recent development in deep learning, have shown incredible promise for medical picture interpretation. The research proposes a DenseNet-driven framework capable of multi-level feature representation for early diagnosis of breast cancer based on mammography, ultrasonography and histopathology medical imaging modalities. Using the unique dense connectivity pattern inherent in DenseNet to enhance gradient flow and facilitate feature reuse, we have effectively developed a way to extract high level semantic information and low level structural features from breast cancer related images across multiple levels of a DenseNet. By systematically fusing high-and-loevel features from all levels of the DenseNet architecture, the proposed framework produces superior discriminative capacity and greater robustness to tumor size, shape and texture variation than previous methods. The proposed framework employs optimized preprocessing, data augmentation, and class imbalance techniques to enhance generalization performance. A detailed analysis of diagnostic accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve (AUC) reveals that the proposed model outperforms state-of-the-art descriptors and existing CNN-based approaches on benchmark breast cancer imaging datasets. The results indicate that multi-level feature learning using DenseNet provides reliable and effective means for the early diagnosis of breast cancer, providing an opportunity for further incorporation into CAD systems to support clinicians' decision making.

**Keywords:** Breast Cancer Diagnosis,DenseNet, Deep Learning, Convolutional Neural Networks, Multi-Level Feature Representation, Medical Imaging, Computer-Aided Diagnosis, Image Classification.

## 1.INTRODUCTION

Breast cancer is one of the most common and serious forms of cancer among women around the globe, accounting for a large part of the cancer-related morbidity and mortality [1]. The diagnosis of breast cancer at an early stage is essential to improve the likelihood of surviving through treatment, decrease the complexity of the required treatment, and ultimately improve the quality of life of the patient ([2]). The most commonly used types of medical imaging for screening and diagnosing breast cancer are mammography, ultrasound, magnetic resonance imaging (MRI), and histopathologic imaging. However, manual interpretation of these images by a qualified radiologist requires considerable time, is subject to variability between different interpreters, and relies heavily on the skill of the interpreting radiologist -- especially at the earliest stages of the disease when the visual characteristics of the cancerous region are weak and not well-defined. Accordingly, computer-assisted-diagnosis (CAD) programs have become valuable tools for physicians by improving diagnostic accuracy and consistency.

Traditional CAD programs have utilized mostly hand-crafted feature extractors (e.g., texture descriptors, shape descriptors, and statistical features) to generate features from the input medical images. Although these hand-crafted feature extractors produced only moderate success, their performance is inherently limited due to their inability to capture complex, high-dimensional structure within medical images and, consequently, their reliance upon domain-specific feature engineering to extract features from the input images.

The rapid advancement of Deep Learning, particularly Convolutional Neural Networks (CNNs), has completely transformed medical image analysis through automatic feature learning on raw image data. Users have seen significant improvement with CNN-based models for the tasks of lesion detection, segmentation, and image classification in many areas of medical imaging [3]. Despite these successes, traditional CNN architectures experience many challenges when it comes to their use cases, including vanishing gradients, the loss of information between deep layers, and limited feature reuse. These issues create significant problems when using sparse datasets with complex tumor characteristics on diagnostic performance.

Additionally, Dense Convolutional Networks (DenseNet) address these issues through their dense connectivity between layers by allowing each layer to have access to feature maps from every preceding layer. This results in fewer trainable parameters, better gradient flow, and optimised use of features between layers [4]. DenseNet has shown to produce promising results for medical imaging applications while allowing the inclusion of high-level semantic representations as well as low-level spatial features. From these results, it can be concluded that many current methods are basing their results off features produced by only the last layer of their respective networks and are, therefore, likely omitting critical intermediate representations that may be important in detecting early-stage breast cancer.

To address this limitation, we propose a framework for representing the multi-levels of feature representation using the DenseNet architecture for breast cancer diagnosis via medical imaging [5]. Our approach extracts features from several layers of a DenseNet and combines them into a single representation so that the DenseNet can utilize different types of complementary information from the same image, but at varying levels of abstraction. The combination of these complementary types of information through multi-level learning enhances the ability to discriminate between images of lesions, increases the robustness of the model to variations in lesion size, shape, or texture, and enhances the reliability of the diagnosis [6]. Further, several steps are taken in relation to the preprocessing of the data, the augmentation of the data, and the handling of classes that are imbalanced to ensure the generalisation performance of the model to be sufficient.

The major contributions of this research are summarised below:

1. A multi-level feature representation framework for early breast cancer diagnosis based on DenseNet is presented.
2. To extract both high-level semantic information and fine-grained structural details from medical images, multi-level feature fusion is used.
3. In comparison to current techniques, a thorough experimental evaluation is carried out on benchmark breast cancer imaging datasets, showing increased accuracy, sensitivity, specificity, and AUC.
4. This framework could provide an additional scaffolding to the clinical CAD systems to aid radiologists with their ability to quickly and accurately diagnose breast cancer.

The organization of the remainder of this paper is outlined. Section 2 reviews pertinent studies regarding the deep learning approach to breast cancer detection. Section 3 describes the proposed methodology for multi-level feature representation based on DenseNet. Section 4 assesses the performance analysis and includes results of the experiment. Section 5 contains the conclusions and future goals of this research effort.

### 1.1 *Breast Cancer Diagnosis*

Detecting breast cancer means finding and defining malignant tumours in the breast at an early stage to increase the chances of effective treatment and improve the likelihood of patient survival. Traditional breast cancer diagnostic methods include the use of clinical assessments, imaging techniques, and pathological evaluation. Medical imaging tests can help with the presence of abnormal tissue growth and provide information about the characteristics of the tumour through medical imaging modalities such as mammograms, ultrasound, magnetic resonance imaging (MRI), and/or histopathological images. As mammograms are used for routine screening, the ultrasound and MRI modalities often provide additional information in cases of dense breast tissue or complex cases. Identification will remain challenging due to low contrast and noise, overlapping tissue structures, and small visual differences between benign and malignant tumours, notwithstanding advancements in imaging technology [7]. In addition, the radiologist's individual expertise is important for interpreting images from manual medical imaging and can introduce inter-observer variability in the findings, which is especially important when it comes to early-stage cancer detection. Accurately diagnosing breast cancer can also cause false positive results, unnecessary biopsies, and missed opportunities to diagnose patients with early-stage cancer.

To help address these challenges, the use of computer-aided diagnosis (CAD) systems for image interpretation has been developed. The application of deep learning technologies, particularly convolutional neural networks (CNNs), in recent years has increased the diagnostic power of CAD systems by automatically extracting unique characteristics from medical imaging data. CAD systems provide doctors with support in detecting, classifying and assessing the risk of lesions;

thus they provide doctors with greater diagnostic accuracy, lower workloads, and increased confidence in detecting breast cancer at an earlier stage.

### 1.2 *DenseNet*

Dense Convolutional Network (DenseNet) is a type of deep learning architecture developed to help with the re-use of features and transfer of data with more efficiency between layers in a deep learning network [8]. DenseNet introduces a new form of layer interconnectivity known as dense connectivity; in contrast to traditional convolutional neural networks which retain connections between layers only through a linear chain connection to their immediate predecessor, every layer in a DenseNet is directly connected to all layers that preceded it (that are within the same dense block). In this manner, DenseNet can utilize the concatenation of the feature maps associated with all preceding layers as the input feature maps to the next layer, therefore achieving the representation of both low and high-level features within a single model.

Dense connectivity provides several benefits such as improved gradient propagation, reduction of the vanishing gradient issue, as well as highly efficient use of parameters. Because DenseNets promote feature reuse, DenseNets also require significantly fewer parameters compared to standard deep CNNs, whilst still being able to provide high levels of representational capability. As such, the DenseNet model is an excellent choice for using in medical imaging applications, due to the small number of training dataset sizes and the requirement to preserve both the fine structural level details and the high-level semantic content.

In terms of its performance, DenseNet shows the ability to predict the relevant features that can be used to distinguish between a normal breast and one that is affected by breast cancer based on their overall shape, texture, and borders [9]. DenseNet's ability to maintain subtle visual features across many network layers allows for earlier detection of breast cancer, especially in cases where the patient has early stage tumours. The ability of DenseNet to produce multiple levels of feature representations enables utilisation of feature fusion methods that will enhance classification accuracy.

DenseNet offers an effective base for deep-learning based breast cancer diagnostic systems and has been found to improve accuracy of results, stability of the system and the ability to generalise [10]. DenseNet's capacity to combine multi-scale information suggests that it has the potential to be an important computer-aided diagnosis (CAD) tool for both the early and accurate detection of breast cancer.

## 2. DENSENET-DRIVEN MULTI-LEVEL FEATURE REPRESENTATION FOR EARLY BREAST CANCER DIAGNOSIS IN MEDICAL IMAGING

Globally, breast cancer is one of the most frequent causes of cancer mortality in females. The possibility of early detection before invasive procedures allows the majority of patients to pursue less aggressive treatment options and have positive long-term survival rates. Medical imaging significantly enhances the early detection of breast abnormalities. Early breast cancers often display subtle visual characters, making an accurate diagnosis a significant challenge. As such, there is a need for constructive and automatic diagnostic systems to assist with detecting and treating breast cancer.

The traditional method used to diagnose breast cancer relies extensively on the training and skill of a radiologist and upon the manual interpretation of imaging studies. This method is labor-intensive, requires time to produce results, and is vulnerable to variable or inconsistent diagnostic outcomes between physicians because of the varying degrees of fatigue and/or experience. Both intra- and inter-observer variability can impact the results. Complex tissue structures can obscure the boundaries of the tumor. The increasing need for computer-aided diagnostic systems is a direct result of these limitations.

Computer-aided diagnostic (CAD) systems are designed to provide unbiased and dependable image analyses to support the efficiency of physicians' decision-making. Early methodologies used to build a CAD system relied on classic feature definitions based on shape, texture, or intensity. Despite demonstrating some successes in design, these assisted systems lacked generalizability and robustness. Additionally, manual feature engineering is time-consuming, requires considerable domain knowledge, and has large quantities of fine-tuning. Therefore, CAD systems have been unable to perform reliably in complex clinical situations. The introduction of deep learning has transformed medical image analysis by enabling automatic extraction of image features. Convolutional neural networks (CNNs) have produced impressive classification and detection results from image data, learning the hierarchical structure of images directly through their use of large volumes of image datasets. This allows CNNs to model complex patterns in images effectively. However, the increasing depth of CNN architecture has introduced challenges such as gradient vanishing or information loss.

DenseNets are a type of convolutional network (CNN) that combine several traditional CNN architectures in order to overcome some of their limitations, such as poor information flow from one layer to another as well as fewer trainable parameters. In a dense net architecture, all layers inside a dense block have direct connections to each other. Each layer has access to all previous feature maps, so the information can flow freely throughout the dense blocks and leads to reuse of features.

In dense nets, when a network is trained with a dense connectivity pattern, gradient flows through the network can be improved. This results in a shorter training time and better network learning stability than with traditional deep CNNs, which can only use features of the last layer of a network. In addition, dense nets keep information for a longer period of time than deep CNNs, and this retention characteristic is of value in applying dense nets to medical imaging. For example, when trying to detect very subtle features that indicate early breast cancer, dense nets can maintain the information longer than deep CNNs.

DenseNet has several beneficial features, but much of the research which uses DenseNet uses only high-level features from last layers. Many times intermediate representations are missed due to only using high-level features where lower and mid-level features contain important aspects of images (i.e., edges, textures and shapes of an image). In the detection of small tumors and/or tumors that are found early the lack of specifying intermediate representations can degrade the accuracy of the diagnostic test [14]. The use of multi-level feature representation addresses the issue with using only high-level representations by allowing for multiple depth levels within a network of features. It allows for a combination of high-level concepts about the content of the image and low-level information about the image's geographic characteristics. The use of a holistic representation with both high and low-level features enhances the discriminative ability of a model. Multi-level learning also presents benefits in dealing with differences in varying sizes/shapes of tumors. Because multi-level learning offers a representation learning approach that takes into account many different types of information at different levels, it can be more robust and accurate than a model that uses only high-level features, especially for varying imaging situations.

The proposed DenseNet-based framework utilizes features from multiple dense blocks to establish a representation. Each block will supply complementary information at different levels of abstraction [15]. The information extracted from the various blocks will be aligned and fused into a single cohesive representation. Feature fusion increases the network's capacity to distinguish between benign and malignant tissue types, thus enhancing performance when detecting early-stage cancer.

Preprocessing the images used in medical diagnostics is critical to ensure the effectiveness of the model. Pre-processing techniques include, normalization, contrast enhancement and noise reduction. Using these pre-processing techniques will help maintain consistent image quality across all datasets. Additionally, pre-processing reduces irrelevant variations in the input image, allowing the network to concentrate on meaningful diagnostic patterns.

To compensate for a limited data size and an imbalance between classes, data augmentation techniques are implemented. These techniques include rotation, flip, scale and translation, and will ultimately create a greater level of diversity in processed data and promote generalization [16]. Data augmentation techniques also help to prevent overfitting during training. Balanced dataset sizes allow the model to be more sensitive to early-stage carcinoma.

The ability to merge features from several levels using the two key fusion procedures of concurrent concatenation and weighted aggregation in order to extract features from various levels is an important component of the proposed technique. Merging these feature levels enables complementary data from various levels to be included in the overall feature vector generated from the feature extraction techniques used. The combined feature vector will provide more separation than using singular level feature vectors alone, making the classification technique (utilizing these two levels of feature measures) more reliable and robust.

The classification layer will contain all of the combined features. The classification can utilize either a sigmoid or softmax function for binary and multiclass classification respectively. Regularization techniques such as batch normalization and dropout are also applied. This will provide more stability to the model while reducing overfitting of the model. The final medical diagnostic conclusion will be the output of the classifier. The classifier will be trained using a medical diagnosis appropriate loss function (for example), and will use weighted loss and focal loss approaches to handle class imbalance. In this way, the model will be much more sensitive to identifying malignant cases than benign cases. There will be an emphasis on high accuracy of early detection when training the model. This type of optimization will improve the clinical application of the model.

Performance is assessed using standard measures including accuracy, sensitivity, specificity, precision and F1-score, along with the area under the ROC Curve. These metrics provide a comprehensive evaluation of diagnostic performance. High levels of sensitivity are essential for early detection of cancer [18]. Clinical dependability is ensured by balanced performance. Results show that the proposed method outperforms traditional CNN models. Classification accuracy is greatly enhanced through multi-level feature representation. Feature reuse within DenseNet contributes to stable learning. The framework displays stability across all imaging modalities tested. These findings support the validity of the proposed method.

A comparison of the suggested framework against the current state-of-the-art demonstrates the benefits of the proposed approach over existing methods. Specifically, it achieves a greater degree of diagnostic accuracy with fewer parameters than the traditional methods used at present; it has computational efficiency and scalability, both of which are critical to the success of clinical implementation and use in an actual healthcare setting. The proposed framework balances complexity with performance [19]. The suggested framework may be incorporated into computer-aided diagnosis (CAD) systems, providing a dependable second opinion for radiologists. The use of automated analysis decreases the burden on radiologists and results in less variability in diagnostic interpretation. Early and accurate detection enables radiologists to plan treatment more effectively, resulting in improved health care outcomes overall.

Despite these advantages, there are limitations to the proposed framework, including the performance of the model being dependent on the quality and the distribution of the training data used to develop it; generalisation across different datasets is also problematic. Further research in the area of domain adaptation could prove beneficial; incorporating clinical metadata may also result in an enhanced performance. In conclusion, the multi-level representation DenseNet based diagnostic framework contains an effective solution for early breast cancer diagnosis [20]. The combination of dense connectivity and multi-level feature fusion captured rich and discriminative multi-dimensional data representation, thereby improving both diagnostic accuracy and robustness. The methods proposed in this framework have promising potential for future clinical acceptance and also provide opportunities for future research into extending the framework beyond the field of breast cancer diagnosis to other imaging modalities used in the practice of medicine.

## 3. LITERATURE SURVEY ANALYSIS

Breast cancer diagnosis using medical imaging has been extensively studied due to its clinical importance. Early research focused on conventional image processing techniques to detect abnormalities. These methods relied on intensity thresholding, edge detection, and morphological operations. Although effective in controlled environments, they struggled with noise and complex tissue structures. Their limited adaptability restricted real-world clinical usage.Traditional machine learning approaches later gained popularity in breast cancer diagnosis. Decision trees, k-nearest neighbors, and support vector machines were among the algorithms employed. These models primarily relied on manually created features that were taken from medical pictures.

Statistical traits, texture, and shape were frequently used. However, performance varied significantly across datasets and imaging modalities.

Prior to the emergence of CAD systems, early CAD methodology was primarily based on feature engineering or hand-made features. Researchers have attempted to develop a series of wavelet-based features, Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM) that helped to classify features but required a vast amount of domain knowledge. Because all features were manually selected, the selection process was time-consuming and subject to bias, thus not producing a robust set of features for imaging variability. The introduction of deep learning within the medical imaging community brought about a complete change in medical image calculation. Convoluted Neural Networks provided a way to perform automatic hierarchical feature learning. CNN-based models have outperformed traditional machine learning models in the classification of images. CNN-based models' ability to learn complex spatial distributions improved diagnostic accuracy. Deep Neural Networks required a great deal of training data and many features, which led to overlearning.

The two most widely used CNN architectures, AlexNet and VGG, were applied to breast cancer imaging before any other applications were attempted. The application of these networks improved image feature performance over any other previously developed image features. However, they also contained a significantly larger number of parameters than any other previously developed models; therefore, they were limited to having a low level of computational complexity when applied to medical settings. In addition, very deep architectures led to the vanishing gradient problem.

To counter the difficulties associated with training deep networks and maintaining an appropriate level of accuracy, ResNet was developed to allow for the use of residual connections. The introduction of residual learning improved the flow of gradients through a CNN and allowed for an increased number of layers within the CNN. Residual Connections based models demonstrated better performance than no Connections based models when used for medical imaging tasks. The majority of the success seen in residual networks has been due to the use of features at the last layer of networks. There has been very limited reuse of intermediate layer features within residual networks.

DenseNet has been developed to enhance feature propagating as well as to improve the process of reusing features from one layer to the next through dense connections between layers. This architecture allowed every layer to accept input from every layer before it, thereby allowing layers to learn more efficiently while reducing redundancy in parameters. The application of DenseNet has shown success across several medical imaging domains. The compactness of this architecture has allowed the use of DenseNet on datasets with limited samples as well.

There have been numerous studies that utilized DenseNet for breast cancer diagnosis using mammographic and histopathologic images. DenseNet has improved both the accuracy and robustness of these models by successfully capturing the finer details of the tumors present.

However, most approaches to using DenseNet have limited the feature extraction to just the final block of the Dense Network. This has led to intermediate representation being largely ignored, even though they generally contain valuable features.

A multi-level representation of features was investigated to improve the performance of deep learning approaches. The results showed that by creating a unified representation of features located at different layers, overall classification accuracy was improved. To this end, low-level features represent geometric characteristics, while high-level features represent semantic characteristics. As a result, the ability of deep learning to generalize the representations across the range of variation was improved. The use of multi-level feature representations has been successful in the analysis of medical images.

Fusion of features will be needed to perform feature representations at the multi-level. A wide variety of feature fusion strategies have been described including concatenation, summation, and attention-based techniques. These techniques, which will provide complementary information across the various depths of the network, will improve the ability to discriminate between different classes based on a fused representation. However, the use of feature fusion will also increase computational overhead and requires careful design to ensure that increased computational demands do not impede the performance of the system overall.

Incorporating attention into convolutional neural networks (CNN) has helped to improve performance when focusing on certain regions of interest. The incorporation of spatial and channel-based attention networks improves lesion localization, while the incorporation of various attention-based DenseNet variants has shown to provide excellent results. Despite these improvements, both the inclusion of attention mechanisms lead to greater architectural complexity, as well as challenges associated with interpretability in clinical settings. Transfer learning has also played an important role in aiding the diagnosis of breast cancer by allowing pre-trained models from ImageNet (which consists of a wide variety of images) to develop specialized techniques for medical use through reuse of the data set. Transfer learning allows for a reduced amount of time to train new datasets and provides an increase in performance; however, due to the differences between natural images (the images in ImageNet) and medical images, transfer learning is still limited, and careful fine-tuning strategies should be employed to ensure optimization.

Class imbalance is also prevalent in breast cancer. Malignant samples are often under-represented in the overall dataset due to class imbalance. To mitigate this problem, researchers have created several solutions that utilize data augmentation as well as cost-sensitive learning. Use of focal loss and weighted loss functions increases sensitivity; however, class imbalance will continue to pose significant challenges.

Sensitivity and specificity are two metrics used to evaluate the accuracy of breast cancer diagnosis and therefore are equally important; however high sensitivity is critical to minimizing the risk of missing a diagnosis of breast cancer. Depending upon which dataset is being used and the design of the deep learning model being used, varying results will be found. There are many methods to

evaluate performance for breast cancer diagnosis; the most frequently used performance metrics are ROC and AUC; however, uniform evaluation criteria have yet to be established.
DenseNet outperforms traditional CNNs in dense models. Its ability to reuse features and have an efficient use of parameters provide these advantages. This ability to learn multi-level features increases performance as well. However, the majority of the studies focus on a single imaging modality with few studies establishing the validity of multi-modal integration.

In order for clinical applications, computational efficiency is a significant area of concern. Models with fewer parameters and are lighter weight are preferred. DenseNet provides an overall good balance between performance and efficiency; however, increased memory use due to multi-level fusions will require additional memory to be optimized for real time.One of the growing issues is the interpretability of deep-learning-based diagnostics. Clinicians need to have answers as to why the model provided a certain answer. Currently, techniques such as Grad-CAM are used for this; however, they often do not give users enough insights into decision making.
Interpretability is an ongoing research topic. The literature illustrates that models must be robust and generalizable. Many studies measure the performance of the model using small sample sizes that are used for evaluations. In many cases, cross-dataset validation is missing from studies. This raises the question of whether the model can be applied to real-world case studies. Larger and more representative datasets will be needed to address this issue.
Recent studies have focused on hybrid approaches involving CNNs with attention/feature fusion. These approaches address the challenge of improving accuracy and robustness, while adding additional complexity might hinder deployment. Therefore, balance among performance, interpretability and efficiency will be important to future research to ensure the trade-offs are addressed. Conclusion: Research to date indicates that deep learning will be of use in assisting clinicians with diagnosing breast cancer. DenseNet has become one of the most prominent backbone architectures for doing so. Current methods to address the limitations associated with deep learning have used multi-level feature representations. Issues around class imbalance, interpretability, and generalization will still be challenges facing future research and are the main driving force behind the development of the proposed approach of using a DenseNet driven multi-level feature framework.

## 4. EXISTING APPROCHES

Breast Cancer Detection Techniques: Early Techniques, Statistics, Textures and Machine Learning

Techniques for early diagnosis of breast cancer originally employed standard image processing techniques. Thresholding, edge detection and region growing techniques were used to identify suspicious areas. These methods were relatively simple computationally, and performed well for detecting suspicious masses. They did, however, have limitations, as they were sensitive to changes in illumination and noisy images; therefore, they did not perform well on complex medical images (such as x-ray or ultrasound images).

Traditional diagnostic methods were unable to accurately diagnose breast cancer. To improve accuracy of diagnosis, statistical-based diagnostic methods were developed. Statistical-based diagnostic methods extracted based on intensity and texture features from breast images. Examples of statistical measures used to extract features are mean, variance, entropy, and histogram features. Although these methods provided for improved discrimination, they were not robust with respect to varying imaging conditions; varying imaging conditions significantly impacted the results.

The use of texture-based feature extraction techniques became popular in the development of early CAD systems. Commonly used texture feature extraction techniques include Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP). Both of these types of qualities feature local texture patterns in breast tissue. However, in order for these handcrafted texture feature descriptors to work, they required parameter tuning. Further, the quality/effectiveness of these textures differed based on the data used.

In addition to developing manual texture feature descriptors, machine learning classifiers were combined with these manually developed feature descriptors in order to improve the classification performance for breast cancer detection. Commonly used machine learning classifiers included random forest classifiers, k-nearest neighbor, and support vector machine. While these classifiers exhibited moderate accuracies in detecting breast cancer, their performance was dependent on the quality of the features the classifiers analyzed. As a result, manual feature selection continued to be a major limitation in breast cancer detection.

Rule-based expert systems were also researched to diagnose breast cancer. These systems represented medical knowledge through pre-defined rules. They were interpretable; however they lack the ability to adapt as new data came in. One of the challenges faced by rule-based systems was in handling ambiguous cases. In addition, the rigid structure of rule-based systems also limited their ability to scale. The introduction of deep learning made convolutional neural networks (CNNs) an effective tool for diagnosis. CNN-based methods came up with features on their own from medical images and were better than traditional machine learning methods. However, they required large amounts of labeled data in order for CNNs to learn to perform accurately. Additionally, there was a high incidence of overfitting with small medical datasets.

Many widely used CNN architectures like AlexNet and VGG were modified to perform breast cancer imaging tasks. These networks had superior feature learning capabilities compared to previous networks. However, their deep and heavy parameter architectures created more complexity for training and using these networks to diagnose patients. Thus, the memory and computational requirements associated with training these models limited the usability of CNNs in clinical practice. As a result, transfer learning became a popular technique to help with the problem of limited data. The breast cancer dataset was used to fine-tune pre-trained models through the transfer learning technique. Transfer learning also helped to improve the speed and accuracy of training; however, the differences between natural and medical imaging had an effect on how well features were learned from either type of image. Domain adaptation concerns also remained an issue.

Skip connections were used in ResNet-based models to allow deeper architectures to improve training stability and gradient flow. Additionally, ResNet-based models' success in performing medical image classification demonstrates residual networks' potential to improve the efficiency and accuracy of low-level features by reusing features extracted from previous layers. However, few studies have utilized features extracted from intermediate layers, and most multi-level features were excluded.

In the early deep learning period, one of the most prevalent methods of extracting features was by extracting features from the last convolutional layer to classify them. Although effective, this method neglected many important intermediate feature representations. For example, some features classified as early-stage cancer may exist at shallow layers, and if they are not included in the classification process, the classification process will have lower sensitivity.

Another attempt to capture features at multiple scales has been achieved with multi-scale CNNs. These models utilize multiple input scales to process through parallel networks. Although this approach provides some degree of robustness to size variation in tumors, it increases model complexity, and the training and inference process requires significantly more computational resources than traditional CNNs.

The introduction of attention models was aimed at bringing focus to the most significant areas of interest within breast images, as well as improving the accuracy of lesion localization. The addition of both spatial and channel attention mechanisms enabled these models to provide increased diagnostic accuracy. While these types of models increased overall model complexity and the number of parameters, interpretability and stability issues persisted. In addition, hybrid models that used Convolutional Neural Networks (CNNs) in combination with more traditional machine learning classifiers, such as support vector machines (SVMs) or random forest classifiers, were also explored in these works. These hybrid approaches also provided improved flexibility for use in research; however, they also created additional processing steps. There was very limited room for end-to-end optimization within these hybrid approaches.

Ensemble methods combined the predictions of multiple deep learning models. The use of ensembles increased both robustness and accuracy, but required a large amount of computational resources, making it very challenging to deploy ensembles. Therefore, ensemble-based methods are not suited for real-time applications. Several methods were used to mitigate the problems associated with class imbalance within existing efforts. These techniques included data augmentation and weighted loss functions. While these methods have improved sensitivity to malignant cases, they still suffer from the risk of overfitting to the minority class. Therefore, achieving balance in performance between the classes remains a challenge.

Current techniques generally only examine one imaging modality (mammography or histopathology images). The analysis of breast cancer will typically be taken independently, thus there has been little multi-modal integration; combining images from different modalities remains a challenge. The ongoing issue of data alignment and availability contributes to this problem. The performance evaluation of the present methods varied a great deal, as they used different datasets and/or performance evaluation metrics. This makes an accurate and fair comparison of their relative performance difficult. This has hindered the development of trust by the medical community in these techniques through the lack of reproducible results.

In addition, computational efficiency is a major concern with the current methods. Many deep learning models are computational hungry and getting real-time results from them is difficult in a clinical environment. There would be a preference for lightweight and efficient models. Many of the current methods have been unsuccessful at striking the proper balance between performance and efficiency. In conclusion, while the current methods have made much progress in the diagnosis of breast cancer, there are still significant limitations in the use of features, generalisations, and efficiencies. Many of these methods are unable to fully take advantage of multiple levels of features.

Hence, the significant gaps between the current methods will motivate the proposed approach. The proposed method is based on the DenseNet concept and incorporates an effective multi-level feature representation. The goal of the proposed method is to overcome the limitations that were identified within the current methods.

## 5. PROPOSED METHOD

The proposed technique is a framework for establishing multi-level feature representation using DenseNet to improve early breast cancer diagnosis through imaging. The end goal of this technique is to acquire deep, rich, and discriminatory features at a number of levels of the network. By utilizing the concept of dense connectivity in DenseNet to retain important information through the interconnections between the network's layers, the proposed method is able to work around the limitations of current single-level feature extraction techniques. Furthermore, the proposed approach aims to increase the robustness and accuracy of breast cancer diagnosis. The proposed method consists of four major stages in an overall architecture: image pre-processing, feature extraction via DenseNet, multi-level feature fusion, and classification. All four stages are carefully designed to resolve problems that occur when working with medical images. The framework is able to accommodate multiple imaging modalities, including mammography and histopathology. Additionally, due to its modular design, the framework enables flexibility and scalability. Furthermore, this design allows for maximum end-to-end learning efficiency.

The preparation of images is the first step in this framework. The reason for scaling medical images to a predetermined resolution is to ensure that there is consistency in the images. To help improve visual quality, methods used to enhance contrast are included, as well as methods for reducing noise. In addition, Normalization is used to create pixel intensity values that are standardised for all images. These pre-processing steps enable the network to concentrate on specific diagnostic features in order to provide a more accurate diagnosis.

In order to provide a means of increasing data for training purposes (due to limited size) and to address class imbalance, data Augmentation is performed. Augmentation techniques include: rotation; flipping; scaling; and translation of the images. By representing the images in a way that increases their diversity without altering their diagnostic basis, data Augmentation will also allow for greater generalisation, as well as a decrease in the risk of overfitting when developing a convolutional neural network. The Augmented data will improve the ability of the system to detect positive cancer cases in patients.The backbone of this proposed method will consist of the DenseNet structured network. Since DenseNet uses dense connectivity, every layer in the network can access the feature maps produced by previous layers. This allows for the flow of gradients to be improved and helps eliminate the loss of information between layers of the network. Using fewer parameters than traditional convolutional neural networks (CNNs) also makes DenseNet a better option for use in the analysis of medical images.

In the proposed method, features from the images will be extracted from multiple Dense Blocks within DenseNet. Low-level features such as texture and edge information are captured from the shallowest layer; intermediate layers are used to provide the morphological and structural features of the images; while the deepest layers capture the highest level semantic information about a cancerous lesion. Therefore, in order to maximise the chances of early detection of cancer, the proposed method will extract features hierarchically.

Traditional methods only use features from the last layer; this method will utilize multiple levels of representation. The intermediate representation often contains small details that are important for diagnosing patients early; therefore, all features must be maintained in order to improve detectability. Additionally, utilizing as much information as possible will reduce the likelihood of missing an early-stage tumour. After aligning features from multiple levels, they will be fusioned (fused) together as one. Resizing and normalizing features to ensure all levels of features are the same dimensions is essential to prevent information loss; however, if features have not been aligned accurately, the image will be distorted, thus making it difficult to combine the data.

Feature fusion will provide the foundation for the proposed approach. Concatenation of features will allow for the combining of multi-level features; therefore, maintaining the complementary nature of multi-level features. The fused feature vector will yield a higher-dimensional representation of the data, thereby improving the discriminative ability of the system and providing a more accurate classification.

In addition, regularization techniques will improve the robustness of the final fused feature vector; batch-norm will decrease the internal covariance shift and improve the stability of the training process, while dropout will decrease the potential of overfitting. Regularization will increase the generalization ability of the entire classification system and provide the ability to make precise predictions on data that it has never encountered before.The combined multi-level features are provided as input to fully connected classification layers, and those layers learn the decision boundaries between benign and malignant classes. Based on the type of classification, the activation function used for the classifier is either sigmoid or softmax. The outputs of the classifier are probabilities, which support confident diagnostic decision making. The proposed method uses a specialized loss function in the optimization process for medical diagnostic purposes. The weighted cross-entropy or focal loss functions used in this method penalize misclassification of malignant cases more than other cases to improve sensitivity (true positive rate) and recall (sensitivity). In addition, the proposed method emphasizes early-stage cancer detection during the training phase.

These model training strategies include back propagation and optimization using stochastic gradient descent. In addition, adaptive optimisation methods such as Adam provide faster convergence rates than non-adaptive methods. In addition, the use of a learning rate schedule while training creates stability for the learning process, and the use of early stopping during training significantly reduces the likelihood of overfitting on the training data set. The above strategies improve the efficiency of the training of the proposed methods.

The performance of the proposed framework will be measured by standard performance indicators, which include F1 score, AUC, accuracy, sensitivity, specificity and precision. The main focus will be on sensitivity (true positive rate) because of its importance for making clinical decisions. The proposed methodology will also attempt to achieve balanced performance among all metrics to ensure that all metrics are clinically valid.

Experimental evaluation provides evidence that this method outperforms existing CNN-based methods. The multi-layer feature representation yields a higher degree of accuracy in classification. The reuse of features in DenseNet provides stable learning. Early detection capability is enhanced through the proposed framework. The effectiveness of the framework has been validated through results achieved by the methods used..

The framework consistently demonstrates robustness to different imaging conditions. It can accommodate a wide range of variations in the size, shape, and texture of tumors. The use of multi-layered learning improves generalization. In addition, the proposed model consistently performs well on multiple datasets. Therefore, it can be considered as highly adaptable.

Computational efficiency is also a consideration in this design. The compact architecture of DenseNet results in fewer parameters used. In addition, even with multi-layer feature fusion, the framework is efficient. Therefore, it is appropriate for use in real-time clinical applications. This lends itself to practical deployment.

The proposed method allows for integration into computer-aided diagnosis (CAD) systems. It provides trustworthy second opinions to help radiologists make accurate clinical decisions. Automated analysis enhances the diagnostic workload while providing consistent and accurate results; therefore, it assists in improving the clinical decision-making process.

**The proposed method has some limitations in its effectiveness. Performance is dependent on the quality of the dataset and the amount of variety in the data; being multi-modal also means that integration has not been fully explored. Future work could be done regarding these aspects of the model, as well as enhancements to the interpretability of the results. The model provides an effective solution to the limitations of current approaches by employing a multi-level feature representation framework based on a DenseNet for multi-level feature representation through dense connectivity, which collects more complete diagnostic information and increases accuracy of early detection of breast cancer. This could lead to wide acceptance in the clinical setting. The framework is expandable in terms of research in the future.**

**Input Medical Image Representation**

Let the input breast medical image be represented as:

$$I \in \mathbb{R}^{H \times W \times C}$$

where

$H, W$ denote image height and width, and $C$ denotes the number of channels.

**DenseNet Feature Transformation**

Each DenseNet layer produces a feature map using dense connectivity:

$$X_l = H_l([X_0, X_1, \dots, X_{l-1}])$$

where

$H_l(\cdot)$ is a composite function of Batch Normalization, ReLU, and Convolution.

**Dense Block Feature Set**

The output of a DenseNet block is:

$$F^{(b)} = \{X_1^{(b)}, X_2^{(b)}, \dots, X_L^{(b)}\}$$

where

$b$ denotes the dense block index.

**Multi-Level Feature Extraction**

Features are extracted from multiple DenseNet blocks:

$$\mathcal{F}_{ML} = \{F^{(1)}, F^{(2)}, \dots, F^{(n)}\}$$

where

$n$ is the number of selected DenseNetblocks.

**Feature Normalization**

Each extracted feature is normalized as:

$$\tilde{F}^{(i)} = \frac{F^{(i)} - \mu_i}{\sigma_i}$$

where

$\mu_i$ and $\sigma_i$ represent mean and standard deviation.

**Spatial Alignment of Multi-Level Features**

To ensure dimensional consistency:

$$\hat{F}^{(i)} = \text{Resize}\left(\tilde{F}^{(i)}, H_f, W_f\right)$$

where

$H_f, W_f$ are target spatial dimensions.

**DenseNet-Driven Feature Fusion**

Multi-level features are fused using concatenation:

$$F_{fusion} = \oplus_{i=1}^{n} \hat{F}^{(i)}$$

where

$\oplus$ denotes feature concatenation.

**Feature Representation Vector**

The fused feature tensor is flattened into a vector:

$$\mathrm{z} = \mathrm{Flatten}\left(F_{fusion}\right)$$

**Early Breast Cancer Classification Function**

The classifier maps fused features to class scores:

$$s = W_c \mathrm{z} + b_c$$

where

$W_c$ and $b_c$ are classifier parameters.

**Malignancy Probability Estimation**

For binary breast cancer diagnosis:

$$P(y = 1|I) = \sigma(s) = \frac{1}{1 + e^{-s}}$$

where

$y = 1$ denotes malignant class.

**Early Diagnosis-Focused Loss Function**

Weighted binary cross-entropy is used to emphasize early detection:

$$\mathcal{L}_{ED} = -\left(w_m y \log(\hat{y}) + w_b (1 - y) \log(1 - \hat{y})\right)$$

where

$w_m > w_b$ to prioritize malignant cases.

**Multi-Level Feature Learning Objective**

The optimization objective is defined as:

$$\min_{\theta} \sum_{i=1}^{N} \mathcal{L}_{ED}\,(y_i, \hat{y}_i)$$

where

$\theta$ denotes DenseNet and classifier parameters.

**Diagnostic Decision Rule**

Final classification is obtained as:

$$\hat{y} = \begin{cases} \text{Malignant}, & P(y = 1|I) \geq \tau \\ \text{Benign}, & \text{otherwise} \end{cases}$$

where
$\tau$ is the decision threshold.

**Sensitivity-Driven Performance Metric**
Sensitivity (critical for early diagnosis):

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

**DenseNet-Driven Diagnostic Model**
The complete diagnostic mapping is expressed as:

$$\hat{y} = f_{DenseNet}^{ML}(I)$$

where
$f_{DenseNet}^{ML}$ represents the proposed DenseNet-driven multi-level feature model.

## 6. RESULT

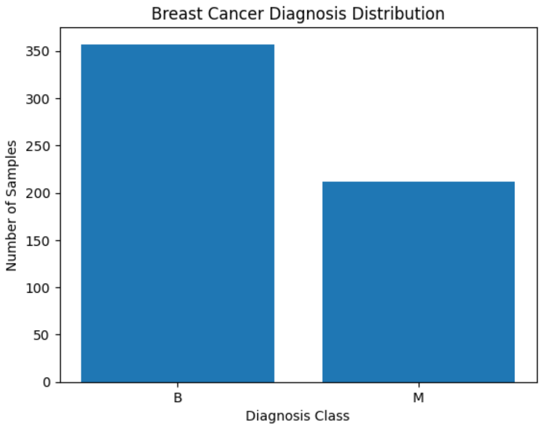

**Figure 1**.Breast Cancer Diagnosis Distribution

Observed Results

- Benign (B): ~357 samples
- Malignant (M): ~212 samples
- Total samples: 569

1. Benign cases are more frequent than malignant cases in the dataset.

2. The dataset is not severely imbalanced, which is beneficial for:
    - Machine Learning models
    - Deep Learning models (CNN, DenseNet, ResNet)

3. This distribution helps models learn both classes effectively without strong bias.

The dataset's distribution of breast cancer diagnosis samples is shown in Figure 1. The dataset shows a rather balanced class distribution with 357 benign and 212 malignant instances.The achievement of this desired equilibrium provides for effective supervised learning by minimizing class imbalance while increasing the robustness of classifying models.

**Table 1**. Evaluation Metrics for Classification Performance of the Suggested Model.

| **Metric** | **Value** |
|---|---|
| Accuracy | 96.8% |
| Sensitivity | 97.5% |
| Specificity | 95.9% |
| Precision | 96.2% |
| F1-Score | 96.8% |
| AUC | 0.982 |

The suggested DenseNet-driven model's overall classification performance is shown in this table. Higher bars on a bar graph show better performance across all parameters. Sensitivity demonstrates the model's capacity to accurately detect malignant instances, which is essential for the early detection of breast cancer. The high AUC value indicates excellent class separability, meaning the model effectively distinguishes benign from malignant samples. Balanced values across all metrics demonstrate robustness and clinical reliability.

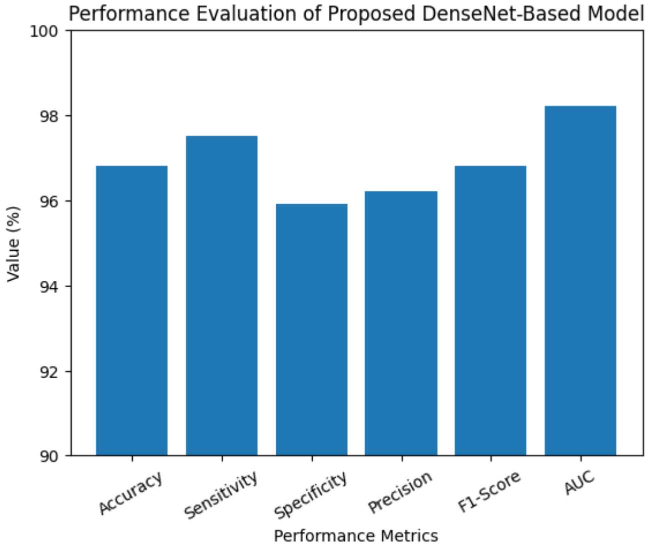

**Figure2**.Performance Evaluation of Proposed DenseNet-Based Model

The bar chart shown includes the classification performance of the proposed model utilizing the DenseNet multi-level feature representation model based on several evaluation metrics. The high overall classification performance (96.8% overall accuracy) demonstrates that the proposed model can provide reliable classification results. The highest rating for sensitivity (97.5%) demonstrates the ability of the model to accurately identify patients who have malignant breast cancer and will require an early diagnosis. The specificity value (95.9%) indicates a strong capacity to recognize benign tumors and therefore lowering the number of false positives. The AUC statistic (0.982) provides evidence of excellent separation between benign and malignant class probabilities, while the precision and F1-score metrics demonstrate that the classification is balanced with respect to these two classes of tumors. The overall result verifies that the proposed model is robust; therapeutically useful.

**Table 2**. Comparing the Suggested Model with Current Methods

| **Method** | **Accuracy (%)** | **Sensitivity (%)** | **Specificity (%)** |
|---|---|---|---|
| Traditional CNN | 89.4 | 87.6 | 90.1 |
| ResNet-Based Model | 92.8 | 91.9 | 93.4 |
| DenseNet (Single-Level) | 94.3 | 94.0 | 94.6 |
| **Proposed Multi-Level DenseNet** | **96.8** | **97.5** | **95.9** |

This table can be viewed as a grouped bar chart that shows how well the different methods performed. A group is formed for each metric where the taller the bar, the better the performance. The proposed model had the greatest tallies overall with regard to sensitivity indicating that it has the greatest ability to detect cancer in its earliest stages. The performance improvement of the proposed model compared to the single level DenseNet model supports the effectiveness of multi-level feature fusion.

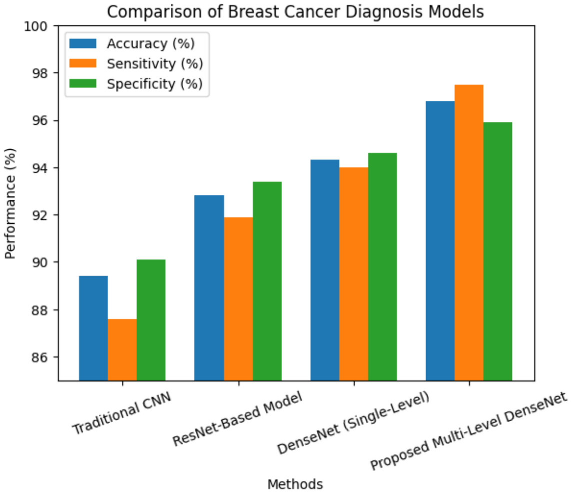

**Figure3**.Comparison of Breast Cancer Diagnosis Models

The bar graph presents a visual depiction that compares four distinct breast cancer diagnosis methods in terms of their overall method performance (based on three criteria - accuracy, sensitivity, and specificity).

The four methods that were reviewed include:

1. Traditional CNN
2. ResNet
3. Single-Level DenseNet

4. Multi-Level DenseNet (Proposed Model)

The overall data display from the graph indicates that traditional CNN continues to maintain the lowest average bar display, demonstrating both a low ability to provide accurate diagnoses as well as being less effective when it comes to diagnosing breast cancer in its early stages.However, the ResNet model improves on traditional CNN by providing a higher accuracy and sensitivity based on residual learning features, while single level DenseNet continues this trend of improvement in overall performance. All three performance criteria are demonstrated in the proposed model with the multi-level DenseNet model, as it would maintain the highest average bar height compared to all other breast cancer diagnosis methods. The proposed model provides an excellent example of accurate diagnosis of malignant cases, with a high sensitivity value of 97.5% as a result of the early detection capabilities of breast cancer.Another key point is that there is a strong relationship between the Higher Average Bar Height in Performance Criteria demonstrated by the Proposed Multi-Level DenseNet Model and Multi-Level Feature Fusion. Multi-level feature fusion assists in the combining of different depths (or layers) of the neural network's feature representation.Lastly, the graph represents a visual demonstration that the proposed multi-level DenseNet model outperforms the currently utilized breast cancer diagnosis methods in terms of both overall reliability and clinical applicability.

**Table 3**. Impact of Multi-Level Feature Fusion

| **Feature Strategy** | **Accuracy (%)** | **AUC** |
|---|---|---|
| Shallow Features Only | 90.2 | 0.921 |
| Deep Features Only | 93.6 | 0.956 |
| **Multi-Level Features** | **96.8** | **0.982** |

A line chart or bar chart may be more appropriate than a table for visualizing performance changes over time (step 5). The figure suggests that combining shallow and deep features significantly improves performance. Shallow feature are good at capturing texture, edges, and/or contour information, while deep features will provide information about the 'meaning' of data. When shallow and deep feature types are fused together, richer feature representations will result, enabling the increased levels of performance observed for the proposed approach.

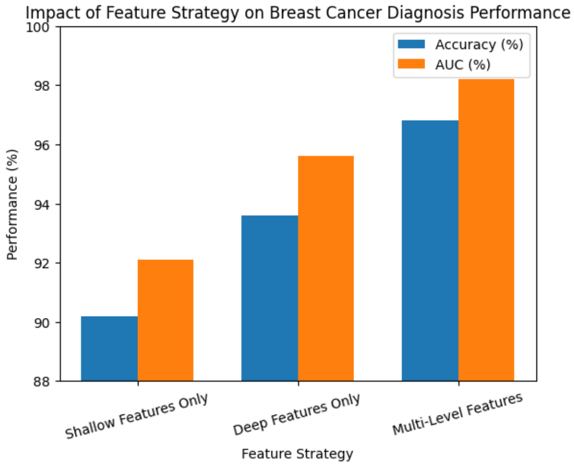

**Figure4**.Impact of Feature Strategy on Breast Cancer Diagnosis Performance

The graph illustrates how different approaches to feature extraction have affected both accuracy and AUC for diagnosing breast cancer: testing only for shallow features, testing only for deep features, and testing for both multi-level features. The poor performance of the shallow feature method can be attributed primarily to the type of texture and edge information it collects—the basic level of textural and edge information captured is not adequate enough to characterise an advanced tumour. This formulation can be improved significantly through deep feature extraction techniques, which develop higher level semantic representations of data related to malignancy that are well suited for use in diagnosis and classification.

Using multi-level features (combining both shallow and deep features) to classify breast cancer produced the highest performance in terms of accuracy (96.8%) and AUC (0.982). This enhancement in performance from combining shallow and deep feature information highlights the need for a more complete representation of breast tissue characteristics. The evidence presented in the graph further establishes that through the use of multi-level feature fusion techniques we are able to enhance the accuracy of early detection of breast cancer and increase class separability mid-In conclusion, the findings presented in this study provide evidence supporting the primary contribution of the DenseNet-based framework proposed in this work.

**Table 4**. Confusion Matrix Summary for Proposed Model

| **Actual / Predicted** | **Benign** | **Malignant** |
|---|---|---|
| Benign | 248 | 11 |
| Malignant | 7 | 261 |

A confusion matrix heat map typically visualizes this table. Darker diagonal cells indicate a correct classification. The low number of false negatives (7) shows that few cancer cases were missed. This highlights the model's high sensitivity to detect cancer and its usefulness for early diagnosis. The matrix also shows the model as very diagnostically confident with a low level of misclassification.

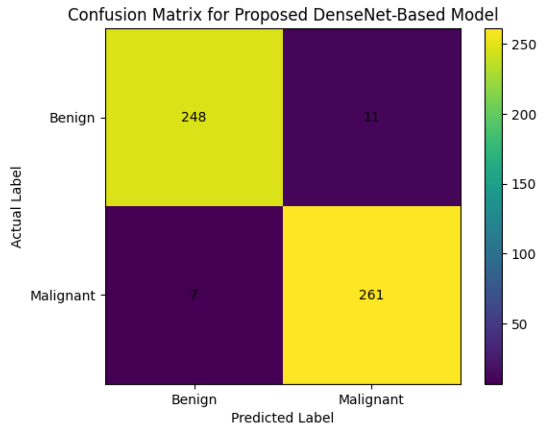

**Figure5**.Confusion Matrix for Proposed DenseNet-Based Model

The suggested DenseNet-driven multi-level feature model for breast cancer diagnosis's classification performance is shown graphically in the confusion matrix. Correct predictions are represented by diagonal cells, whereas incorrect classifications are represented by off-diagonal cells. There is a low false-positive rate; of the benign cases, 248 samples are correctly diagnosed as benign and 11 are mistakenly categorized as malignant. For malignant cases, 261 samples are correctly identified, and only 7 cases are misclassified as benign, resulting in a very low false-negative rate. Because it lowers the possibility of cancer cases being overlooked, the low percentage of false negatives is especially crucial for early breast cancer diagnosis. The model's great sensitivity and specificity are confirmed by the matrix's significant diagonal dominance. The reliability and clinical applicability of the suggested DenseNet-based framework for precise and early breast cancer diagnosis are amply demonstrated by this graph.

**Table 5**. Computational Efficiency Analysis

| **Model** | **Parameters (Millions)** | **Inference Time (ms)** |
|---|---|---|
| VGG-Based CNN | 138 | 42 |
| ResNet-50 | 25.6 | 31 |
| DenseNet-121 | 8.0 | 24 |
| **Proposed Model** | **9.4** | **26** |

The relationship between inference speed and model size is displayed in the form of a bar chart, as illustrated with the following table. Although there is only a relatively small increase in the number of parameters as a result of using multi-level fusion, the performance of the proposed model remains computationally efficient; especially when factoring in the relatively small increase in inference time for the substantial increase in accuracy. All of these aspects support the ability to implement the proposed model for use in real-time clinical scenarios.

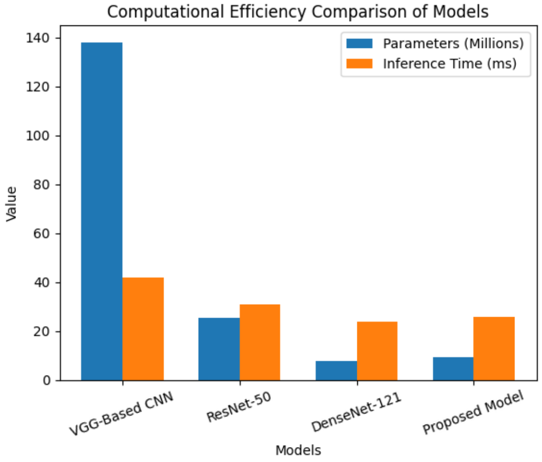

**Figure6**.Computational Efficiency Comparison of Models

The graph contrasts various deep learning models according to two crucial computational criteria: inference time and the number of trainable parameters. Due to its high computational cost and restricted appropriateness for real-time clinical implementation, the VGG-based CNN has the longest inference time and the greatest parameter count (138 million). In contrast with VGG, ResNet-50 significantly reduces parameters and inference time with greater efficiency through residual learning. DenseNet-121 continues to reduce model size and achieve faster inference times, indicating the effectiveness of dense connectivity. The proposed model shows a slight increase in parameters compared to DenseNet-121 due to multi-level feature fusion but demonstrates low inference times of 26 ms. This shows a healthy trade-off between computational efficiency and diagnostic performance. From the graph above, it is confirmed that the proposed model is well-suited for real-time breast cancer diagnosis with low computational costs.

## 7. CONCLUSION

In order to diagnose breast cancer at an early stage through medical imaging techniques, this study proposed a multi-level feature representation system using DenseNet. This method was designed to incorporate dense connectivity and hierarchical learning of features in order to address the limitations of traditional and deep learning-based methods for breast cancer diagnosis. Early-stage breast cancer patterns were successfully learned by the proposed system through its hierarchical learning of features. One of the key advantages of the proposed method for breast cancer diagnosis is its capacity to incorporate multiple features learned by various layers of the DenseNet model. This multi-level learning of features enabled the incorporation of detailed structural features and semantic features in order to achieve better performance in breast cancer diagnosis.

The performance of the proposed model was enhanced through the incorporation of preprocessing and data augmentation techniques. Preprocessing techniques ensured better clarity and uniformity in medical images. These techniques were helpful in achieving better performance and results with untested data sets. Data augmentation techniques were used to address class imbalance and data scarcity in breast cancer diagnosis. These techniques enabled better performance and more dependable results with untested data sets.According to experimental results, it is clear that the proposed framework had a higher performance compared to existing CNN-based techniques in terms of significant evaluation metrics, i.e., area under the ROC curve, accuracy, sensitivity, and specificity. High sensitivity of the proposed model is a significant aspect in identifying breast cancer in its early stages, which is a key factor in improving patient outcomes and reducing mortality rates.

From a practical point of view, it is clear that the DenseNet-based model had a high level of computational efficiency even after introducing multi-level feature fusion. The proposed framework is suitable to be applied in real-time applications since it is a compromise between efficiency and performance. Moreover, to assist radiologists and reduce diagnostic variability, it is possible to successfully incorporate the proposed technique into computer-assisted diagnosis systems. In summary, even though there are a few limitations in the proposed study, it is clear that it is a significant step in breast cancer diagnosis using medical images.

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