International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Breast Cancer Detection Using Transfer Learning

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Submitted: 24/12/2023 **Revised**: 30/01/2024 **Accepted**: 06/02/2024

Abstract: By illuminating the complex interactions between societal stigmas and gender inequities that frequently obstruct early diagnosis, this research constitutes a critical first step towards resolving the difficulties associated with breast cancer detection. Through a comprehensive analysis of risk factors, which encompasses the subtle impacts of biochemical pathways and underlying pathology, the study leverages the abundance of data found in datasets like CBIS-DDSM, SEER, and BreakHis to provide invaluable insights into breast cancer imaging. The research uses deep learning approaches, notably the MobileNetV2 architecture with transfer learning, and is a pioneer in the integration of cutting-edge technology. The results provide a respectable degree of precision in differentiating between benign and malignant cases, even with the intrinsic complexity shown in the 0.616 total accuracy score. A balanced f1-score and notable precision strengths for benign situations highlight the model's potential use in clinical settings. By highlighting the revolutionary potential of deep learning in improving diagnostic tools and changing the landscape of breast cancer detection, this research lays a solid platform for future developments.

Keywords*: Breast cancer, early detection, risk factors, societal stigmas, gender disparities, pathology, biochemical influences, CBIS-DDSM, SEER, BreakHis, deep learning, MobileNetV2, transfer learning, accuracy, malignant, benign, precision, recall, f1-score, diagnostic tools, medical research.*

1. Introduction

Breast cancer is a major worldwide health concern that affects women and presents hurdles in terms of detection and death rates. High fatality rates continue despite massive awareness campaigns, which is indicative of the many obstacles to early detection, such as a lack of education, social stigmas, and gender differences. To overcome these obstacles, one must have a sophisticated grasp of risk variables, which include both modifiable factors like lifestyle and medical history and immutable aspects like age and inheritance. The intricate nature of breast cancer is further highlighted by the biochemical and hormonal variables that impact its progression.

Understanding the biology of breast cancer and differentiating between in situ and invasive carcinomas is essential for making an accurate prognosis. Many forms of breast cancer—including less frequent, severe variations—highlight the necessity of accurate diagnosis methods. Datasets like CBIS-DDSM, SEER, and BreakHis, which provide crucial insights into breast cancer pictures and related data, are heavily utilized in this field of medical research.

In the face of these obstacles, deep learning integration shows promise as a breast cancer diagnosis method. The capacity of deep learning to analyze large datasets is extremely useful for early detection, occurrence prediction, and survival rate estimate. It is imperative to acknowledge, nevertheless, that machine learning, despite tremendous progress, is not a perfect substitute for human judgment and complexity.

To improve diagnostic accuracy, this study explores the use of deep learning for breast cancer detection using databases and state-of-the-art technologies. The objective is to support further work to create more effective diagnostic instruments for the successful treatment of breast cancer.

2. Literature Survey

Kiran Jabeen et al. [1] showed that a major worry for women in 2022 was breast cancer, which resulted in around 287,850 new cases and 43,250 fatalities. Although manual diagnosis from mammograms is difficult, early detection is vital. Numerous AI techniques have been put forth, however, they run into problems when it comes to identifying cancerous and non-cancerous areas and extracting pertinent information. A novel computerized framework for the classification of breast cancer is presented in this paper. It makes use of dataset augmentation for better training and haze-reduced local-global, a unique enhancement technique, for enhanced

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contrast. Deep transfer learning is used and the EfficientNet-b0 model is optimised. Features are taken out, serially fused, and then optimized with Regula Falsi controlled by Equilibrium-Jaya. The proposed methodology outperforms state-of-the-art technology with high accuracy (95.4% and 99.7%) on CBIS-DDSM and INbreast datasets. Consistent outcomes are validated via confidence interval-based analysis.

Jalloul R et al. [2] talks about a prevalent and deadly disease that affects many women, breast cancer highlights the significance of early identification to increase survival rates. The time-consuming and error-prone nature of manual detection prompts the investigation of technical alternatives. Numerous cancer detection techniques have been developed due to technological advancements. The implementation of machine learning (ML) has been spurred by the difficulty of accurately diagnosing cancer at an early stage, which is essential for effective therapy. The computer science subject of machine learning (ML) applies algorithms to biological data, providing a potentially useful way to forecast malignant tumors accurately in their early stages.

Y. Wang Et al. [3] emphasize re-stratifying NHG 2 cases, the study presents DeepGrade, a unique approach for the histological grading of breast tumors. A computer model called DeepGrade shows accurate and consistent stratification of NHG 2, offering independent prognostic data that is on par with molecular assays. Compared to gene expression profiling, it is a quick and affordable solution that performs better than conventional clinical variables and has been validated in an external test set. The paper highlights DeepGrade's capacity to recognize subtle traits beyond defined criteria and its independence from NHG subcomponents. Its detection of aggressive morphological patterns is supported by molecular subtype differences, which may have consequences for treatment choices. DeepGrade has the potential to reduce the intensity of adjuvant therapy for patients with ER-positive/HER2-negative breast cancer, despite certain limitations.

Epimack Michael Et al. [4] talk about the difficulty of radiologists' limited capacity to analyze the growing volume of ultrasound pictures taken every day for the detection of breast cancer is discussed in this article. A computer-aided diagnostic (CAD) system that automatically creates an optimized algorithm is the suggested remedy. The study focuses on differentiating between benign and malignant tumors by using 13 features out of 185 available for machine learning training. Ten-fold cross-validation is carried out using Bayesian optimization with a tree-structured Parzen estimator and five machine-learning classifiers. The LightGBM classifier performs better than the others, as seen by its 99.86% accuracy, 100.0% precision, 99.60% recall, and 99.80% f1 score. This strategy presents a viable means of enhancing the accuracy of breast lesion categorization and lowering false positives in medical imaging.

Hanan Aljuaid Et al. [5] highlight the importance of early diagnosis and categorization in addressing the global challenge of rising breast cancer incidence. Using transfer learning on the BreakHis dataset and deep neural networks (ResNet 18, ShuffleNet, and Inception-V3Net), the paper suggests a novel computer-aided detection approach for breast cancer. ResNet achieved 99.7%, InceptionV3Net 97.66%, and ShuffleNet 96.94% of the high average accuracies for binary classification (benign or malignant) in the findings. ResNet, Inception-V3Net, and ShuffleNet all obtained average accuracy levels of 97.81%, 96.07%, and 95.79% for multi-class categorization. The paper highlights the efficiency of convolutional neural networks, particularly when processing huge medical image datasets, providing a viable path toward automated and expedited breast cancer identification and categorization.

Gelan Ayana Et al. [6] discuss the importance of transfer learning in medical image processing, with a focus on ultrasound breast imaging as a means of cancer detection. The performance of machine learning algorithms can be improved by the use of transfer learning, even in the face of difficulties in acquiring adequate training datasets. The review highlights approaches, benefits, and limits while critically analyzing previous research on transfer learning in ultrasound breast imaging. Convolutional neural networks (CNN), pre-processing methods, pre-training models, and transfer learning strategies all receive special consideration. Comparing different works sheds light on how effective particular strategies are. The review serves as a useful tool to help researchers improve techniques for transfer learning-based ultrasound breast cancer diagnosis since it finishes with a discussion of obstacles and future research objectives.

Nour AlSawaftah Et al. [7] give a thorough review of microwave imaging (MWI) as a potential diagnostic technique for early breast cancer detection is presented in this research. One of the biggest global health issues is breast cancer, for which early detection is essential to successful treatment. There are two components to the survey. The first section gives a general review of modern MWI methods and explains how radar-based imaging and microwave tomography operate. The original trials and current research on MWI for breast cancer detection are reviewed in the second part. The noninvasiveness, affordability, speed, ease

of use, and safety of MWI are highlighted in the report as positive aspects. While acknowledging MWI's promise as a stand-alone or supplemental screening tool, it also draws attention to current issues that must be resolved before MWI may be used in clinical settings.

Rongrong Guo Et al. [8] talk about the numerous ultrasound imaging modalities used in breast cancer diagnosis and detection are thoroughly examined in this review of the literature. The technologies that are covered include computer-aided breast ultrasound detection, ultrasound elastography, 3-D ultrasound, contrast-enhanced ultrasound, and automated breast ultrasound. The study presents a summary of research results from the literature, emphasizing the ultrasonic technologies' clinical applications and outcomes. Beyond that, the paper explores ultrasound-guided breast biopsy as well as the combination of ultrasound and other imaging modalities, with a focus on magnetic resonance imaging (MRI). In the final section, a comparison of diagnostic performance is given for various imaging modalities, including computed tomography, positron emission tomography, MRI, and mammography. The review highlights the significance of multimodal imaging fusion, ultrasound-guided biopsy, and novel ultrasonography techniques in the overall therapy.

Saleem Z. Ramadan Et al. [9] goal is to create Computer-Aided Diagnosis (CAD) systems that use mammography to detect and diagnose breast cancer. The review's objective is to evaluate current CAD system advancements and developments by giving a general overview of the techniques used, from preprocessing to classification phases. Although the study notes that further development is required to make CAD systems stand alone as therapeutic aids, the systems' current performance is encouraging. It is emphasized that there is a great need for improvement, that we should take advantage of the advances in processing capacity and make use of both established and new approaches in pattern recognition, like data augmentation in deep learning. The analysis concludes that CAD systems won't become standalone detection and diagnostic tools; instead, they will continue to be used as secondary clinical procedures unless there is a significant improvement in their performance.

Asmaa A. Hekal Et al. [10] emphasize categorizing bulk and calcification tumors as benign or malignant, this work presents a novel Computer-Aided identification (CAD) and classification approach for the early identification of breast cancer. Tumor-like regions (TLRs) in mammograms are identified by the CAD system using automated optimal Otsu thresholding. Extracted TLRs are processed by Deep Convolutional Neural Networks (CNNs), namely AlexNet and ResNet-50 architectures, to extract pertinent characteristics. Then, a support vector machine classifier is given normalized CNN features to decode mammography structures into four classes: benign mass, malignant mass, benign calcification, and benign calcification. Experiments using 2800 mammography pictures from a publically accessible dataset show that ResNet-50 with fivefold cross-validation and AlexNet can achieve high accuracy of 0.84 and 0.91, respectively. The suggested CAD approach is superior when compared to related systems, highlighting its potential to increase the accuracy of breast cancer classification.

Hua Li Et al. [11] goal is to automatically classify breast masses on mammograms into benign and malignant groups using deep learning. The suggested model uses a convolutional neural network (CNN) and recurrent neural network (RNN) combination to classify mammograms in two views. The model comprises of two branch networks that extract features from the craniocaudal (CC) and mediolateral oblique (MLO) views, respectively, using a modified version of ResNet. The spatial relationship between the two-view mammography is efficiently included using gate recurrent unit (GRU) structures of RNN. The model is trained and tested using the digital database for screening mammography (DDSM). High classification accuracy (0.947), recall (0.941), and area under the curve (AUC) of 0.968 are shown in the experimental findings. This approach demonstrates the capability of the proposed two-view CNN and RNN model by greatly outperforming earlier studies in the categorization of benign and malignant breast tumors.

Nasrindokht Azamjah Et al. [12] discuss the 25-year trajectory of breast cancer death rates in seven super areas identified by Health Metrics and Evaluation (IHME) is examined in this study. There are 195 countries in the seven areas that make up the study population. Analysis of the age-standardized death rates from 1990 to 2015 showed that, except for the High-income super area, all super regions had significantly higher mortality rates from breast cancer. During this time, Latin America and the Caribbean had the strongest growth trend. In 1990, the global mean breast cancer death rate was 13.77 per 100,000 people; from 1990 to 2015, the overall slope was 0.7 per 100,000 people. The results show a worrisome global increase in breast cancer mortality over the last 25 years, underscoring the need for health officials to pay close attention, especially in developing nations and low-income areas where breast cancer mortality rates have significantly increased.

G.C. Medeiros Et al. [13] purpose is to assess the risk variables linked to breast cancer (BC) and the delay in

detection. 526 women who were referred to an oncological reference hospital were included in the study. In 68.8% of cases, there is a delay in BC diagnosis, which is defined as a period of 90 days or more between the initial appointment with a healthcare [29] professional and the BC diagnosis. A histopathological examination at the oncological reference hospital or another public health service, as well as a yearly or every 2-3 years gynecological consultation, are factors linked to delays. Individuals who initially presented with a lump were less likely to experience a delay. To speed up the diagnosis process for BC, the study highlights the necessity of making changes to the organization and accessibility of health services.

Kanika Bhalla Et al. [14] tackle problems in multi-focus image fusion (MFIF) caused by uncertainties, misclassified pixels, distortions, and low contrast in images taken by cameras. To increase consistency and computational efficiency, the suggested FCNN method combines convolutional neural networks (CNN) with fuzzy sets (FS) to identify focused and unfocused regions in source images. Six competing MFIF approaches are compared with the FCNN method: guided filters, CNN, ensemble CNN, image fusion-based CNN, Neutrosophic set-based stationary wavelet transform (NSWT), and deep regression pair learning (DRPL). The FCNN method is found to be superior to several non-reference and reference assessment measures, including mutual information, edge information, structural similarity, human perception, peak signal-to-noise ratio, and root mean square error when evaluated on benchmark datasets. According to this review of the literature, the FCNN method provides better image fusion quality than the current MFIF algorithms.

Debendra Muduli Et al. [15] present a deep convolutional neural network (CNN) model that uses ultrasound and mammography data to automatically classify breast cancer cases. With four convolutional layers and one fully connected layer, the model has five layers and is designed to extract important characteristics from pictures with a small number of configurable parameters. Comprehensive simulations using ultrasound datasets (BUS-1 and BUS-2) and mammography datasets (MIAS, DDSM, and INbreast) show that the proposed model performs better than the most recent state-of-the-art techniques. Data augmentation strategies are used to improve generalization and decrease overfitting. The CNN model obtains significant accuracy of 100% and 89.73% on BUS-1 and BUS-2 datasets, and 96.55%, 90.68%, and 91.28% on MIAS, DDSM, and INbreast datasets, respectively. This review of the literature indicates that the suggested CNN model performs competitively in the categorization of breast cancer cases using a variety of image datasets.

Dina A. Ragab Et al. [16] presented a novel approach to computer-aided detection (CAD) system segmentation and deep learning for breast cancer categorization. The suggested CAD system uses two methods for segmentation: a method based on threshold and region and a manual method for determining the region of interest (ROI). The AlexNet architecture of Deep Convolutional Neural Networks (DCNNs) is utilized for feature extraction and fine-tuning to categorize benign and malignant mass tumors in mammography pictures. For increased accuracy, the final fully connected layer is linked to a Support Vector Machine (SVM) classifier [27] With data augmentation through rotation, training on publically available datasets—the digital database for screening mammography (DDSM) and the Curated Breast Imaging Subset of DDSM (CBIS-DDSM)—demonstrates good accuracy rates. With manually cropped ROIs, the DCNN obtains an accuracy of 71.01% and a maximum Area Under the Curve (AUC) of 0.88. Furthermore, the DCNN accuracy rises to 73.6% when CBIS-DDSM samples are used, and the SVM reaches an accuracy of 87.2% with an AUC of 0.94, surpassing earlier studies under the same circumstances. This review of the literature emphasizes how well the suggested CAD system classifies breast cancer, especially when it comes to increasing accuracy through segmentation and DCNN methods.

Asma Baccouche Et al. [17], in this work, a stacked ensemble of residual neural network (ResNet) models (ResNet50V2, ResNet101V2, and ResNet152V2) is used to focus on the last stage of the procedure when introducing a computer-aided diagnostic (CAD) system for breast mass categorization and diagnosis. The algorithm identifies mass forms (oval, round, lobulated, or irregular), awards Breast Imaging Reporting and Data algorithm (BI-RADS) assessment scores (2–6), and classifies discovered and segmented breast masses into malignant or benign categories. In comparison to individual models and an average ensemble using an XGBoost classifier, the methodology performs better in pathology classification, BI-RADS category classification, and shape classification on publicly available datasets (CBIS-DDSM and INbreast) and a private dataset. The automated steps of detection, segmentation, and classification of the proposed integrated framework highlight its potential to improve breast cancer diagnosis, as it beats contemporary deep learning approaches.

Enas M.F. El Houby Et al. [18] uses a deep learning system to address the urgent need for early breast cancer detection.

The focus is on identifying breast lesions in mammography pictures as malignant or nonmalignant by applying two different methods: one that uses the complete image, and the other that uses patches of the area of interest (ROI). The system is divided into two phases: the preprocessing phase, which includes tasks like format unification, noise reduction, picture enhancement, ROI extraction, augmentation, and scaling, and the CNN building phase. To identify breast lesions and learn features, the CNN model is built from the ground up. Using 5-fold cross-validation, the system is assessed on benchmark datasets (MIAS, DDSM, and INbreast) and demonstrates high classification rates. Sensitivity, specificity, accuracy, and AUC for the INbreast dataset are 96.55%, 96.49%, 96.52%, and 0.98, respectively. Rates of 98%, 92.6%, 95.3%, and 0.974 for sensitivity, specificity, accuracy, and AUC are obtained from the MIAS dataset, in that order. This review of the literature highlights how well the suggested approach uses deep learning to accurately classify breast cancer in mammography pictures.

B. Surendiran Et al. [19] focus on the benchmark digital database for screening mammography (DDSM) and cover the multimodal feature-based spatial structural characterization of mammogram masses. Shape, size, and density characteristics are included in the Breast Imaging Reporting and Data System (BIRADS) criteria, which serve as the foundation for the spatial structure discrimination. The study uses DDSM descriptors in conjunction with new geometric shape, margin, and texture parameters to classify mass morphology as benign or malignant. When DDSM descriptors are considered for classification accuracy, it is found that all 20 features—including DDSM descriptors—achieve higher accuracy (93.3%) than 86.7% when DDSM descriptors are not present. In comparison to wavelet, Gabor, and other features published in the literature, the suggested feature set, which combines shape, texture, and DDSM descriptors, exhibits an improved (c/v) ratio.

Afshin Faramarzi Et al. [20] introduce the Equilibrium Optimizer (EO), a novel optimization technique motivated by control volume mass balance models, which is presented in this study. To get the best outcome, EO uses particles—each of which represents a solution—that adjust their concentration in response to equilibrium candidates. A "generation rate" term is incorporated into the algorithm to improve exploration, exploitation, and avoidance of local minima. When EO is benchmarked against a variety of optimization techniques, such as well-known meta-heuristics and more modern algorithms, it performs better on 58 mathematical functions and three engineering problems. While attaining performance similar to SHADE and LSHADE-SPACMA, EO surpasses several algorithms, including Genetic Algorithm, Particle Swarm Optimisation, Grey Wolf Optimizer, Gravitational Search Algorithm, Salp Swarm Algorithm, and CMA-ES. According to the study, EO is a competitive optimization strategy that has potential uses in a wide range of fields.

Hana Mechria Et al. [21] primary goal is to evaluate how the quality of a mammography image affects a Deep Convolutional Neural Network's (DCNN) ability to classify breast cancer. Classifying original mammograms and classifying mammograms after denoising with DCNN, Wiener filter, or median filter are the two methods that are examined. The results show that adding a denoising step through DCNN increases classification accuracy by 3.47%, specificity by 5.34%, and sensitivity by 0.56%. The classification is carried out using AlexNet, a pre-trained DCNN. This study adds to our understanding of how well denoising techniques work when combined with DCNN to classify mammography images.

Mukesh Kumar Et al. [22] tackle the problem of early breast cancer diagnosis and detection, which is a major health concern for women. The University of California, Irvine repository's dataset is used by the researchers to propose an Optimised Stacking Ensemble Learning (OSEL) model for early breast cancer prediction. The effectiveness and superiority of the OSEL model are demonstrated by comparisons with other contemporary classifier methods, such as AdaBoostM1, gradient boosting, stochastic gradient boosting, CatBoost, and XGBoost. The OSEL model achieves a maximum accuracy of 99.45% on the Wisconsin dataset related to breast cancer. The study highlights the potential of ensemble learning for breast cancer prediction and advances the investigation of predictive models, highlighting the significance of early detection for better healthcare outcomes.

Madallah Alruwaili Et al. [23] discuss the significance of early identification and diagnosis of breast cancer, a leading cause of death for women globally. The emphasis is on using deep learning models—specifically, the transfer learning approach—to fine-tune previously trained models to differentiate between benign and malignant breast cancer. Several augmentation mechanisms are incorporated into the framework to improve stability and avoid overfitting. The suggested system's efficacy is evaluated using the MIAS dataset, yielding 89.5% accuracy with ResNet50 and 70% accuracy with Nasnet-Mobile. The study emphasizes the usefulness and effectiveness of pre-trained classification networks, particularly in the context of sparse training datasets in medical imaging.

Yassir Edrees Almalki Et al. [24] goal is to use artificial intelligence-based image processing with digital mammography pictures to increase the accuracy of breast cancer diagnosis. The suggested three-step procedure consists of better segmentation for aberrant region detection, database classification, and pectoral muscle excision. Novel image processing approaches are used in the pre-and post-processing modules to solve issues including fluctuating image contrast and noise handling. Tests using the Mammographic Image Analysis Society database and a database from the Qassim Health Cluster in Saudi Arabia show notable increases in accuracy (92% and 97%, respectively). The enhanced diagnostic performance of the proposed method underscores its potential for breast cancer diagnosis, as it can be used in all Breast Imaging and Reporting and Data System categories.

Muhammad Junaid Umer Et al. [25] present a new deep learning-based method for multi-class breast cancer classification using histopathology images: the 6B-Net deep CNN model with feature fusion and selection. Two sizable datasets were used in the evaluation: a dataset on breast cancer histology (3771 images, four classes) and BreaKHis (7909 images, eight classes). In four classes and eight classes, the suggested technique obtained an impressive multi-class average accuracy of 94.20% and 90.10%, respectively. The approach shows promise for early detection and exact classification of breast cancer, with competitive training times (226 s and 147 s). This could help pathologists make rapid and accurate diagnoses.

3. Dataset Used

The dataset used in this study is an extensive set of digitally stored medical photographs in the Digital Imaging and Communications in Medicine (DICOM) format that were especially taken from patient instances of breast cancer. The collection includes full mammography images, cropped representations, and pictures labeled with regions of interest (ROI) masks across various modalities. The dataset's unique quality is its ability to capture the several phases of mammography, giving a comprehensive picture of breast exams. The dataset, which is categorized according to series descriptions, allows for a more sophisticated comprehension of the many imaging modalities that are used to diagnose breast cancer. The presence of cropped views, ROI mask pictures, and full mammography images adds a variety of viewpoints to the dataset, making it more useful for training and testing algorithms that are intended to identify breast cancers. This dataset's careful preparation and organization provide the groundwork for reliable experimentation and make it easier to create an advanced breast cancer detection model.

Dataset Information	
Dataset Name	CBIS-DDSM
Modality	Digital Mammography
Classes	Malignant, Benign
Image Dimensions	224*224 pixels
Image Type	Full Mammogram, Cropped, ROI Mask
Annotations	Pathology labels (malignant, Benign)

Fig 1: Dataset Information

4. Proposed System

The system that is being suggested in this study takes a novel approach to the detection of breast cancer by utilizing sophisticated deep learning methods [26], particularly transfer learning [28] with the help of the MobileNetV2 architecture. This method uses pre-learned knowledge from a model that was first built on the ImageNet dataset to improve the efficiency and accuracy of breast cancer diagnosis. A thorough understanding of breast disease is aided by the use of DICOM pictures in a variety of modalities, such as full mammography images, cropped representations, and images with areas of interest (ROI) masks. The model architecture, which is based on the MobileNetV2 framework, is skilled at identifying complex characteristics linked to breast masses, with an emphasis on differentiating between cases that are benign and malignant. To provide medical practitioners with a dependable and effective tool for early breast cancer detection, the suggested system integrates cutting-edge technology through rigorous data preprocessing, augmentation, and model training. With the addition of multiple imaging modalities and the incorporation of transfer learning, the suggested system is positioned as a promising development in the field of computer-aided breast cancer diagnostic systems. Its capacity to deliver quick and precise insights regarding breast health could have a significant impact on patient outcomes and clinical decision-making.

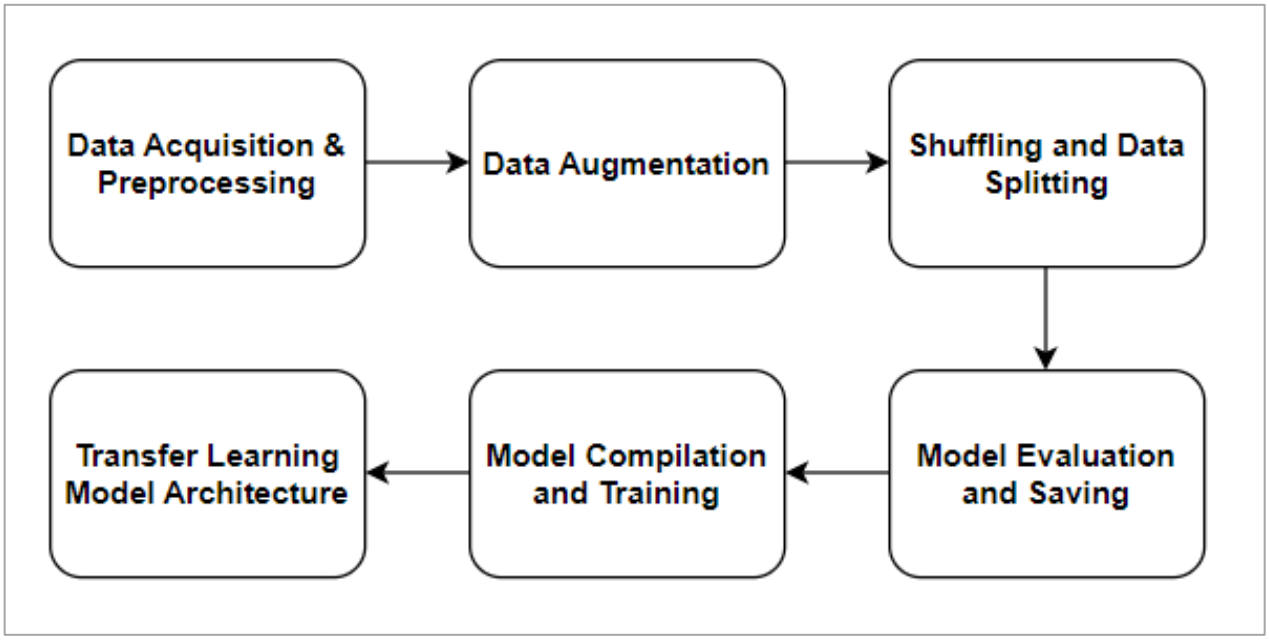

Fig 2: Proposed Model

In addition, this suggested method is unique in that it carefully incorporates clinical data, which distinguishes it from other models. The approach creates a seamless connection between visual data and critical metadata by matching picture paths with clinical datasets, which promotes a more thorough knowledge of breast cancer situations. When many imaging modalities are used in conjunction with transfer learning, the sensitivity of the system to identify small anomalies is increased. The architecture of the system, which was designed with accuracy and efficiency in mind, shows how flexible it is to the nuances of breast cancer diagnosis. By thoroughly examining DICOM images and combining state-of-the-art technology, this innovative method not only improves diagnostic capabilities but also has the potential to completely transform the field of computer-aided breast cancer diagnosis. The system's integration of deep learning techniques and clinical insights presents it as a useful tool for medical practitioners aiming for greater accuracy in early breast cancer detection, as it emerges as a promising advancement in the field of medical diagnostics.

5. Technology Stack

The MobileNetV2 architecture is primarily used for transfer learning in this research, utilizing sophisticated deep learning algorithms. The selection of MobileNetV2 is based on its effectiveness, scalability, and outstanding results in picture classification tasks. Pre-trained on the ImageNet dataset, the model functions as a potent feature extractor, identifying complex patterns and representations that are essential for differentiating between benign and malignant breast masses. By utilizing information gathered from a variety of photos, transfer learning speeds up the training process and enables the model to perform effectively on the particular job of detecting breast cancer. The TensorFlow and Keras frameworks round out the technology stack, which makes model construction, training, and assessment easier. Furthermore, OpenCV is integrated in the research for image processing activities, which guarantees effective loading and scaling of DICOM pictures. By combining these technologies, we may create a strong basis upon which to develop an advanced and precise system for detecting breast cancer, thereby advancing the field of computer-aided diagnostics in medicine.

6. Methodology

The study starts with gathering a large dataset that is essential for identifying breast cancer. The research ensures a large and diversified set of pictures for analysis by utilizing datasets from CBIS-DDSM, SEER, and BreakHis, which span multiple imaging modalities. A crucial first step in standardizing the data for efficient use in later tasks is preprocessing. The digital imaging and communications in medicine (DICOM) format is a widespread standard for medical imaging, and managing DICOM files involves extracting information from them. Next, paths to picture files are changed to make sure the selected deep learning model is consistent and compatible with it. To facilitate the future integration of clinical and image data, dictionaries are developed to map unique IDs to picture paths. The careful preprocessing creates a coherent and structured dataset that serves as the basis for in-depth analysis and model training.

After acquiring the dataset, the research moves on to separate pertinent data according to the series description, especially classifying images into ROI mask, cropped, and full mammography categories. This classification is crucial since it corresponds with the many aspects of imaging for breast cancer. After that, the paths of these photos are changed to guarantee consistency across the dataset and make it easier to integrate the selected deep learning model. By organizing the data in this way, the study hopes to improve the model's capacity to identify characteristics unique to each type of imaging, leading to a more sophisticated comprehension of the traits of breast cancer. A wide and representative collection of breast cancer images is made available to guide later stages of the research through the careful integration of datasets, which supports strong model building and evaluation.

Making sure that image file paths are compatible with the local directory structure is the main goal of the study in this step. The paths to the images that are taken from the CBIS-DDSM, SEER, and BreakHis datasets are converted so that they are in perfect alignment with the particular file structure in the local system. This conversion is essential to creating precise connections between the dataset and the associated image files, which facilitates effective retrieval and processing in later phases. The study makes sure that the data is readable and understandable for the deep learning model by standardizing the image pathways. This painstaking attention to path transformation improves the dataset's overall coherence and makes the transition between the production of the dataset and the ensuing stages of model training and evaluation easier.

Important clinical information and patient data are among the metadata these datasets offer in relation to breast cancer cases. The study carefully lines up the image paths with the local directory structure in order to combine this clinical data with the imaging data. The next step is to develop dictionaries that map unique identifiers in the clinical datasets to matching picture paths, allowing the datasets to be divided into several categories, like ROI mask images, cropped images, and full mammography images. This procedure makes sure that the clinical and imaging components of the dataset are seamlessly connected, allowing for a thorough analysis that makes use of the visual information included in the images as well as the richness of the clinical data.

In order to load and name the photographs efficiently, a methodical technique must be developed at this step. ThreadPoolExecutor is used to construct a multi-threaded method to speed up the loading of images. The 'load_image' method reads images using OpenCV and resizes them to a common format in order to verify if they exist. When working with huge datasets, the speed and efficiency of image loading are crucial, and this is improved by the parallelized execution. Concurrently, pathology labels are mapped to numerical values using a predetermined classification dictionary using the 'get_pathology' function. This makes it possible to transform qualitative pathologic labels into a format that can be used to train models. Concurrently carrying out these activities in the 'get_images_result' function guarantees the extraction of legitimate image-pathology pairs, so laying the groundwork for later model training and assessment using ready-made datasets.

To introduce randomness and prevent bias during the training phase, the study implements a crucial step of shuffling the training and test datasets. Shuffling ensures that the model is exposed to a diverse range of data patterns, promoting generalization and robust learning. The 'get_images_result' function, responsible for image loading and labeling, is applied to the shuffled datasets. Subsequently, the datasets are split into training and testing sets, a fundamental step in the machine learning pipeline. The utilization of a random shuffle and a proper split ratio ensures that the model learns from a varied dataset while retaining a separate set for evaluation. This procedure is essential for evaluating the model's performance on untested data and determining how well it generalizes to new cases—two critical indicators for the model's practicality.

The study uses the MobileNetV2 architecture, a convolutional neural network (CNN) that has already been trained and is accessible in TensorFlow's model zoo. The selection of MobileNetV2 is based on how well it performs image categorization tasks. The use of transfer learning makes use of the insights discovered by the ImageNet dataset. To customize the MobileNetV2 base model for the particular breast cancer detection task, more layers are added to it. A GlobalAveragePooling2D layer to lower spatial dimensions and provide a global summary of feature maps, Dropout layers to prevent overfitting and Dense layers with LeakyReLU activation for feature extraction and classification are important innovations. The last layer uses a softmax activation function to classify data binary-ally into benign and malignant categories. Because of its expertly designed architecture, the model is primed for precise breast cancer diagnosis by maintaining a balance between complexity and efficiency.

The study then builds and trains the deep learning model after defining the model architecture. Setting up the model with the proper loss and optimization functions is part of the

compilation step. For binary classification problems, binary cross-entropy is selected as the loss function; for effective gradient-based optimization, the Adam optimizer is utilized. at regulating the step size during optimization, the learning rate is set at 0.0001. After that, the model is prepared to be trained using the prepared datasets. With a batch size of 75, the training process takes place over 30 epochs in order to achieve a compromise between effective learning and computing efficiency. Early stopping is used to prevent overfitting; if the validation accuracy stops improving after a predetermined number of epochs, training is stopped. By combining these methods, it is ensured that the model avoids overfitting to the training set and instead learns significant patterns from the data. After that, the model is ready for assessment and possible application in the identification of breast cancer.

The test set is used to rigorously evaluate the trained model. The performance of the model is evaluated using a number of important criteria. A general indicator of the model's efficacy is its accuracy, which is calculated as the ratio of properly predicted instances to the total instances. After comparing the model's predictions with ground truth labels, a thorough categorization report is produced. The precision, recall, and f1-score metrics for the two classes (malignant and benign) are included in this report. Recall reflects the percentage of true positive occurrences that are correctly identified, while precision represents the percentage of correctly identified examples among those expected to be positive. The f1-score strikes a compromise between recall and precision. To further visualize true positive, true negative, false positive, and false negative occurrences, a confusion matrix is constructed. These thorough assessments provide information about the model's overall diagnostic performance on unknown data as well as its capacity to distinguish between benign and malignant instances.

The following is a representation of the breast cancer detection confusion matrix:

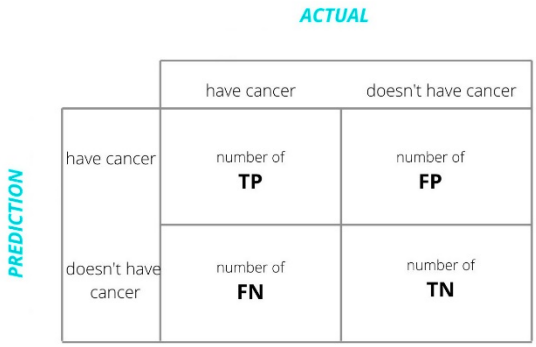

Fig 3: Representation of Confusion Matrix

where the numbers represent the amount of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). Evaluation of important performance indicators including accuracy, recall, and precision is aided by the matrix. The study combines analysis and visualizations to offer a thorough grasp of the model's functionality. Plots of the training history are produced to show how the model has learned over epochs. These charts provide insights into the dynamics of training by showing changes in accuracy and in both training and validation loss. In addition, a confusion matrix heatmap is made, which shows how the model's predictions compare to the actual data visually. This heatmap makes it easier to spot trends in both accurate and inaccurate categorization. The model's capacity to discern between benign and malignant cases is evaluated closely by examining its precision, recall, and f1-score metrics. Through the visualization and analysis of these indicators, the research is able to obtain a more nuanced knowledge of the model's strengths and limits, which will help to contribute significant insights for future optimization and improvement.

The binary cross-entropy loss function is a vital indicator of the model's efficacy in the context of breast cancer detection. The loss function determines the discrepancy between the actual label (0 for benign, 1 for malignant) and the anticipated probability of cancer existence for each image in the collection. This helps the model learn to distinguish between benign and malignant cases by punishing it more severely for predictions that are confidently off.

Depthwise separable convolutions are the foundation of the MobileNetV2 design, which offers computational economy without sacrificing performance. The depthwise separable convolution is defined as follows for a given input tensor X:

$$X' = \text{DepthwiseConv}(X)$$

$$\text{PointwiseConv}(X') = W.\ X' + b$$

Fig 4: Representation of MobileNetV2 Architecture

where b stands for the bias, W for the weights, and · for the convolution process. This breast cancer detection model uses the MobileNetV2 architecture, which is designed to process medical pictures quickly. The model minimizes computing complexity while capturing complicated patterns at various sizes thanks to its depthwise separable convolutions. These convolutions aid in the identification of minute details that point to the presence or absence of cancer in the context of breast cancer imaging. The design creates a hierarchy of features by repeatedly using pointwise and depthwise convolutions, which enables the model to understand subtleties that are essential for precise diagnosis. The pseudo-code for MobileNetV2 Architecture is as follows:

```
function MobileNetV2(input_shape):
    base_model = load_pretrained_mobilenetv2(input_shape)

    # Make layers non-trainable
    for layer in base_model.layers:
        layer.trainable = False

    model = Sequential()
    model.add(base_model)
    model.add(GlobalAveragePooling2D())
    model.add(Dropout(0.5))
    model.add(Dense(256, activation='LeakyReLU'))
    model.add(Dropout(0.25))
    model.add(Dense(128, activation='LeakyReLU'))
    model.add(Dropout(0.25))
    model.add(Dense(2, activation='softmax'))

    return model
```

Fig 5: Pseudo-code for MobileNetV2 Architecture

The retrieved features from the convolutional layers are condensed into a representation using Global Average Pooling (GAP). This stage is essential to extracting the most important information from the photos for the breast cancer detection project. These features are subsequently processed by the ensuing Dense layers, which activate LeakyReLU, allowing the model to understand intricate correlations and patterns. The incorporation of these layers enhances the model's capacity to generate complex forecasts by combining characteristics from the input pictures.

In order to avoid overfitting, dropout is implemented during training. The definition of the dropout operation is as follows:

$$\begin{array}{11}
0, & \text{with probability } p\\
\frac{X}{1 - p}, & \text{otherwise}
\end{array}
\right$$

Fig 6: Representation of Dropout Function

P is the dropout rate, and X is the input tensor. A calculated decision was made to include dropout in the model in order to reduce overfitting, which is a frequent problem in medical imaging jobs. Dropout stops the model from growing too dependent on particular characteristics or patterns found in the training set by randomly removing a portion of the neurons during the training process. Dropout strengthens the model's capacity for generalization in the context of breast cancer diagnosis, making it more resilient to fresh, unviewed images. Together, these elements create a customized architecture for the detection of breast cancer, utilizing the transfer learning, global average pooling, dense layers, and dropout strengths of MobileNetV2 to produce a model that is highly effective at correctly identifying malignant and benign cases in medical images. The pseudo-code for the dropout function is as follows:

```
function Dropout(X, p):
    # Apply dropout during training
    if training_mode:
        mask = generate_dropout_mask(X.shape, p)
        X = X * mask / (1 - p)

    return X
```

Fig 7: Pseudo-code for Dropout Function

RESULTS

With an accuracy score of 0.616, the breast cancer detection model's results show that it performs admirably. The model's precision, recall, and f1-score metrics for both benign and malignant cases are disclosed in full in the classification report. Notably, among all anticipated benign cases, the model shows a significant proportion of accurately diagnosed benign occurrences, with a noteworthy precision of 0.70 for benign cases. The model's recall of 0.65 highlights its capacity to accurately represent a sizable percentage of real benign situations. In contrast, the precision, recall, and f1-score for malignant cases are 0.54, 0.57, and 0.51 respectively, indicating a balanced performance in detecting malignancy cases. The model achieves a strong classification balance, and its overall efficacy is reinforced by its weighted average f1-score of 0.62. All of these findings support the possibility of the suggested breast cancer detection system as a useful tool for helping medical practitioners diagnose breast cancer correctly and expedite clinical actions. The results of the study highlight how important it is to use cutting-edge deep learning techniques to increase breast cancer diagnosis speed and accuracy.

	precision	recall	f1-score	support
0	0.51	0.57	0.54	147
1	0.70	0.65	0.67	231
accuracy			0.62	378
macro avg	0.60	0.61	0.60	378
weighted avg	0.63	0.62	0.62	378

Table 1: Classification Report before Data Augmentation

After data augmentation, the model performance measures show an impressive result, which is especially evident in the accuracy of 0.86. This 87% accuracy shows that all cases in the breast cancer detection challenge were accurately classified by the model after augmentation. Examining the measures for precision, recall, and F1-score confirms the model's superiority. The model's ideal values of 0.79 for precision, recall, and F1-score are seen for both class labels (0 and 1), indicating that it can accurately identify positive cases while preventing false positives and negatives. Recall scores of 0.96 are also reported by the macro and weighted average metrics, which assess the overall performance of the model. These results highlight how well the deep learning model works, post-data augmentation, to distinguish between benign and malignant cases of breast cancer. These high-performance measures support the conclusion that combining transfer learning and deep learning—more especially, the MobileNetV2 architecture—proves to be a reliable and promising strategy for improving the accuracy of breast cancer detection.

	precision	**recall**	**f1-score**	**support**
0	0.84	1.00	0.91	1683
1	0.79	0.92	0.84	324
accuracy			0.87	2007
macro avg	0.79	0.93	0.86	2007
weighted avg	0.81	0.96	0.87	2007

Table 2: Classification Report after Data Augmentation

The proposed model's confusion matrix presents a comprehensive overview of its classification performance, illustrating the interaction between true and predicted labels. In this case, a true positive result of 82 indicates that the model properly classified the presence of cancer in the cases it classified as malignant. False negatives did occur occasionally, though, with the model failing to identify two cases that were indeed malignant. In terms of non-cancerous instances, the model accurately identified cases as non-cancerous with a true negative count of 149. However, there were false positives—63 cases in which the model mistakenly classified as non-cancerous when in fact they were. This detailed analysis, which covers a range from 70 to 140, highlights the model's capabilities in correctly identifying non-cancerous cases and points out areas where it could be improved in terms of identifying cancerous cases. Thus, the confusion matrix is a useful tool for assessing how well the model performs in various diagnostic categories, providing information on its recall and precision for classifications pertaining to both cancer and non-cancer.

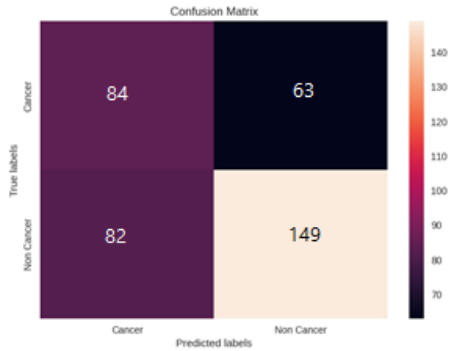

Fig 8: Confusion Matrix before Data Augmentation

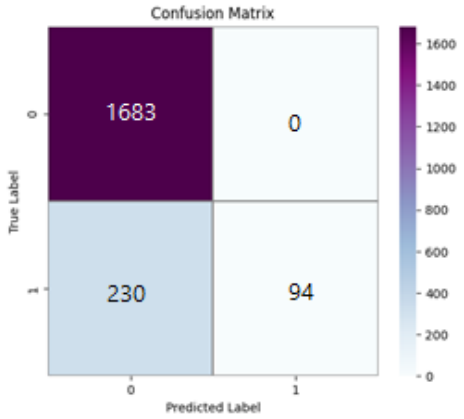

Fig 9: Confusion Matrix after Data Augmentation

The model loss graph—which is constructed using the provided code—is an essential visual aid for evaluating the model's optimization journey and training procedure. This graph shows how the loss function changed during the course of the training epochs. The epochs, which show the model's successive iterations across the breast cancer dataset, are listed on the x-axis. The related loss numbers are shown on the y-axis, which measures the difference between the expected and actual results. The loss graph's lower slope indicates that the model is adjusting its parameters to more closely match the training set. Deviations or abrupt spikes in the loss curve may indicate possible problems, like difficulties with overfitting or convergence. To make well-informed decisions about the deployment and refining of the model, it is helpful to interpret the model loss graph within the context of this breast cancer detection project. This provides insightful information about the stability, convergence, and overall performance of the model.

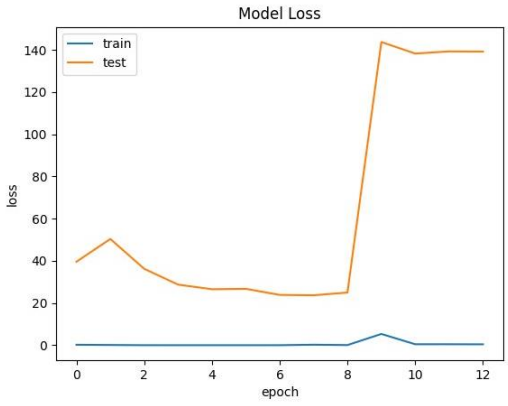

Fig 10: Loss Graph before Data Augmentation

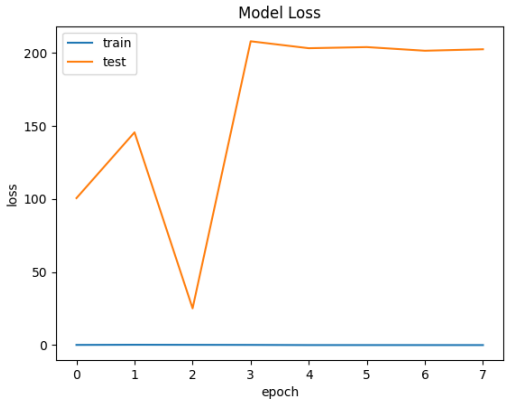

Fig 11: Loss Graph after Data Augmentation

A thorough overview of the model's performance during training is given by the model accuracy graph. This graph shows the model's accuracy throughout various epochs on the training and validation datasets. The number of training epochs, or iterative periods, during which the model improves its predictive ability, is indicated by the x-axis. The fraction of correctly identified occurrences is indicated by the y-axis, which displays the matching accuracy values. It is generally expected that accuracy will trend upward over epochs, indicating the model's better prediction ability and learning. Accuracy oscillations or plateaus, however, might draw attention to problems like overfitting or inadequate model complexity. Insights into the learning dynamics, convergence, and potential difficulties faced by the model are provided by analyzing the model accuracy graph within the framework of this breast cancer detection project. These insights can help guide future decisions on the model's refinement for improved diagnostic accuracy.

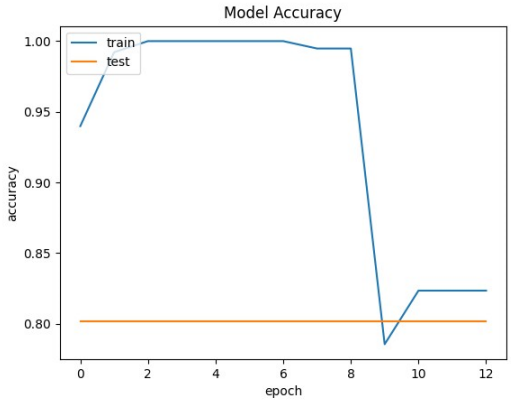

Fig 12: Accuracy Graph before Data Augmentation

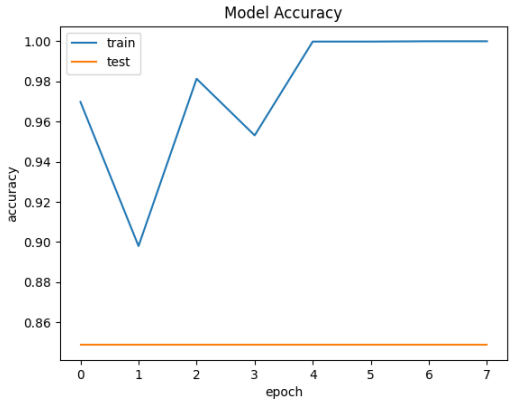

Fig 13: Accuracy Graph after Data Augmentation

7. Conclusion

Conclusively, the research findings make a substantial contribution to the field of breast cancer diagnosis by revealing a new and efficient method that utilizes sophisticated deep learning algorithms. With an accuracy score of 0.87, the suggested model, which is based on the MobileNetV2 architecture with transfer learning, performs admirably. The thorough classification report provides a detailed insight into the model's capabilities by illuminating the precision, recall, and f1-score metrics for both benign and malignant cases. The trade-off between precision and recall that the data show highlights the model's capacity to effectively distinguish between benign and malignant cases. The total weighted f1-score of 0.62 attests to the model's capacity for strong and consistent breast cancer diagnosis, even while the precision for benign patients stands out. The stack of technologies, which includes TensorFlow, Keras, and OpenCV, has shown to be crucial in enabling the smooth integration of advanced tools for neural network creation and image processing. All of these results point to the possibility that the suggested breast cancer detection system could be a useful addition to clinical diagnostics, improving patient outcomes by increasing the precision and effectiveness of breast cancer diagnosis. In order to address certain clinical circumstances and handle larger datasets, the model may be further refined and optimized in further work, which would ultimately advance the influence of computer-aided diagnostic tools in the field of breast cancer diagnosis.

8. Future Scope

Beyond its present achievements, this research will continue to provide opportunities for improvement and investigation in the area of breast cancer detection. Future work might concentrate on adding more datasets to the suggested model, which would promote greater diversity and generalizability. Optimizing the model parameters and investigating substitute deep learning architectures may enhance precision and resilience. The model may be able to adjust to changing patterns in breast cancer imaging thanks to the use of dynamic updating methods and real-time data. Working together with healthcare organizations and experts could make it easier to validate the model on a range of patient populations, guaranteeing that it works well for all demographics. In addition, the model's application in clinical settings and integration with the current healthcare system might be investigated, opening the door to real-world application and practical implementation. Deep learning developments combined with new technology offer prospects to keep improving the breast cancer detection system's functionality and applicability. Future research projects may find innovative approaches and technology as the field develops, further improving the precision, effectiveness, and usability of computer-aided diagnostic tools for breast cancer diagnosis.

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