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Leveraging Faster CNN (F-CNN) for Effective Breast Cancer Classification

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Abstract

Within the scope of this work, a novel classification method for the diagnosis of breast cancer that is based on deep learning is also described. In this particular instance of breast cancer, which is the most common form of cancer in females, early detection is absolutely necessary in order to get better treatment outcomes. Notwithstanding their effectiveness, traditional diagnostic techniques have drawbacks such high expenses and possible errors. The high dimensionality and instability in tumor morphology that are particular problems with breast cancer imaging are intended to be addressed by the suggested techniques. Using publically available datasets for rigorous training and validation, a bespoke deep learning model is designed and implemented, and an extensive evaluation of current deep learning methodologies is conducted as part of the research. The model's accuracy and resilience are significantly improved when compared to the performance of existing classification algorithms. To enhance diagnosis accuracy in the characterization of breast cancer, this study makes utilizes of deep learning, more especially faster convolutional neural networks. The investigation also looks at the model's clinical usefulness, providing information about how it might be incorporated into diagnostic procedures. According to the findings, it appears that the highlighted methodology has the potential to transform the diagnosis of breast cancer by offering a dependable and automated solution that can improve early detection and patient outcomes. In just 3 epochs, the model obtained a remarkable accuracy of 92% on DDSM dataset.

Keywords: Deep Learning; Breast Cancer; Convolutional Neural Network; Disease Detection.

1. Introduction

Breast cancer is still one of the most typical and deadly illnesses that impact women globally [1]. Breast cancer is the most typical form of cancer that affects women all over the world. Based on the World Health Organization (WHO), breast cancer accounts for around 25 percent of all cases of cancer that occur in women. Early diagnosis improves survival rates and lowers death by greatly increasing the likelihood of a successful course of therapy [2]. The task of correctly identifying and categorizing breast cancer in its early stages remains extremely difficult, even with advancements in medical imaging and diagnostic tools. Clinical examination, mammography, ultrasound, and biopsy have historically been the mainstays of the diagnosis of breast cancer. These frameworks have several drawbacks, even though they work well; these include expensive prices, restricted application in low-resource environments, and the possibility of false positives or negatives. Patients diagnosed with breast cancer (BC) with tumors smaller than 10 mm have a 98% chance of surviving the disease. Cancer survival is closely connected with the size of the tumor at the time of diagnosis. Seventy percent of cases are diagnosed when the tumor is thirty millimeters or higher [3]. Computational techniques, especially those based on artificial intelligence (AI), have become a viable way to enhance current diagnostic processes in recent years. Deep learning (DL) stands out among these because of its capacity to automatically learn and extract features from large datasets, resulting in increased accuracy in image analysis applications.

A branch of computer learning called "deep learning" uses multi-layered neural networks to simulate intricate patterns and representations in data [4]. With its unmatched performance in tasks like picture segmentation, classification, and detection, its application in medical imaging has transformed the area. In particular, convolutional neural networks have proven to be remarkably efficient in processing medical images, which has led to their popularity in the recognition and categorization of breast cancer. Obstacles include the high dimensionality of medical pictures, the variable appearance of tumors, and the requirement for extensive, annotated datasets for model training. Furthermore, to assure the clinical translation of deep learning models' dependability and safety in real-world situations, extensive validation is needed.

This work uses deep learning techniques to create a faster classification system for the recognition of breast cancer. By improving the effectiveness and precision of breast cancer diagnostics, this research aims to enhance patient outcomes and early breast cancer detection. The proposed work use deep learning approaches to address the unique problems related to breast cancer identification, given the field's rapid improvements and proven success in a variety of fields. The recommended methodology will be created to get beyond the drawbacks of conventional diagnostic techniques and provide a more automatic and dependable method of classifying breast cancer. This research provided a Faster CNN Model (FCNN), which is a framework that depends on deep learning and is built for the specific characteristics of breast cancer images. The goal of this study is to make a contribution to the expanding body of knowledge in the area of medical image analysis. The system correctly identify between moderate and cancerous breast lesions using cutting-edge deep learning architectures and algorithms. This would lessen the workload for radiologists and increase the precision of diagnoses. The following is an outline of the key contributions that has been made by this study paper:

- Analyze different deep learning methods for breast cancer categorization to assess their advantages, disadvantages, and overall suitability.
- Incorporate data augmentation methods for the purpose of enhancing the functioning and robustness of the classification model.
- Develop a tailored deep learning-based classification model (F-CNN) specifically for breast cancer identification.
- Train and validate the proposed model using publicly available breast cancer datasets to evaluate its accuracy and generalizability.

The remainder of the study is structured as follows: Section 2 presents a literature review, Section 3 details the materials and methods, Section 4 discusses the experiments and findings, and Section 5 offers conclusions and suggestions for future scope.

2. Literature Review

This section offered a thorough analysis of recent findings and developments in the field of deep learning-based breast cancer categorization. The aim of this study is to examine a variety of methods and approaches that have been implemented in order to enhance the accuracy and efficiency of breast cancer identification and diagnosis.

Allugunti Viswanatha Reddy et al. [5] (2022) proposed the use of Computer-Aided Diagnosis (CAD) to categorize patients into three groups: those with cancer, those without cancer, and those with non-cancerous diseases. The study investigated the functionality of three renowned classifiers in the classification process: Random Forest, Support Vector Machine, and Convolutional Neural Network. This study reveals that pre-processing leads to more accurate and dependable diagnostic outcomes by improving image quality prior to categorization. To ascertain how well these classifiers work in differentiating between the given patient categories, a detailed analysis is conducted. Additionally, the study highlights the need of pre-processing mammography pictures, which is critical to raising the classification success rate. The results emphasize the value of picture pre-processing in obtaining improved classification accuracy and show the potential of CNN, SVM, and RF classifiers in creating reliable CAD systems in order to recognize and diagnose cancer.

Iqbal M.S et al. [6] (2022) used a specific dataset to build a deep learning system for breast cancer recognition and classification. They used a transfer learning techniques along with convolutional neural networks (CNNs) to build a robust model that can accurately identify cancerous tissues. Although specifics of the dataset were not stated in the summary, the authors employed a dataset related to breast cancer. Because precession was a crucial performance indicator for assessing the system, the model architecture was designed to maximize performance in that area. It is particularly crucial to emphasize that the model can use pre-tested networks thanks to the use of transfer learning, which improves performance even with little datasets. By providing a highly accurate and computationally efficient model for breast cancer detection, this research advances the field and demonstrates the potential of deep learning approaches, especially in conjunction with transfer learning, for medical image analysis.

Ramesh S et al. [7] (2022) developed a revolutionary deep-learning architecture that combines machine learning methods with tumor segmentation to classify tumors as either cancerous or not. By precisely determining the type of tumors, a process that has historically relied on expert annotations and pathology reports, the suggested method improves doctors' ability to make decisions. Following segmentation, the performance of several classifiers, such as Support Vector Machine, Decision Tree, Random Forest, and Naïve Bayes, is optimized. When compared to traditional methods, the study shows that this strategy greatly improves classification accuracy, as well as sensitivity, specificity, Jaccard and Dice coefficients. Tumor segmentation is handled through the GoogLeNet architecture, which efficiently addresses the difficulty of requiring considerable expert input. In particular, model demonstrates an average increase of 4.61% above current techniques and a 3.78% boost in accuracy over the AlexNet classifier. These findings highlighted the utility of combining machine learning classifiers with deep-learning architectures such as GoogLeNet to gain more accurate and consistent tumor identification.

Ammar Mohamed et al. [8] (2022) offered numerous significant advances to the field of breast cancer identification utilizing images from biopsy microscopy. At first, it presented a deep learning method using different kinds of deep convolutional networks to identify breast cancer. The impacts of various data pretreatment techniques on the functionality of these deep learning models are investigated in the study's second portion, emphasizing the significance of data preparation for improving model accuracy. Thirdly, to improve the performance of classification even more, the study offers an ensemble approach that combines the top-performing models. Moreover, this study's introduction of the ensemble learning technique enhanced the models' precision even more, with the greatest accuracy reaching 92.5%. These results demonstrated how well deep learning models work when divided with ensemble techniques, data preprocessing, and biopsy images for enhanced breast cancer diagnosis.

Sharma T et al. [9] (2022) looked into how well convolutional neural networks (CNNs) and transfer learning worked together to dividing breast cancer images. They used the datasets that are freely accessible to the public, such as BCDR-F03 and Mini-MIAS, which include mammography pictures used to diagnose breast cancer. To increase performance on the grouping tasks, the authors used a CNN-based architecture that was improved by transfer learning and made use of pre-trained models. In comparison to more conventional machine learning techniques, the study highlights the effectiveness of integrating transfer learning with CNNs because it not only increases accuracy but also uses less processing power. According to the findings, this technique is quite successful at classifying images of breast cancer, which makes it a useful tool for clinical diagnostics. In light of the possibility that big annotated datasets may not be available in real-world medical settings, the authors conclude that their technique provides a solid and trustworthy means of identifying breast cancer.

Kavitha T et al. [10] (2022) presented a novel approach to the diagnosis of breast cancer through the utilization of digital mammography tools. Optimal Multi-Level Thresholding-based Segmentation with DL-enabled Capsule Network (OMLTS-DLCN) is the name given to this particular method. An initial processing stage known as Adaptive Fuzzy-based median filtering (AFF) is utilized by the model in order to accomplish the objective of reducing noise from mammography pictures. This model used the Shell Game Optimization (SGO) method in conjunction with Optimal Kapur's Multilevel Thresholding (OKMT-SGO) in order to facilitate the separation of breast cancer. In order to acquire a reliable diagnosis of breast cancer, a Back-Propagation Neural Network (BPNN) and a feature extractor that is based on CapsNet are applied. The results of the studies, which highlight the efficiency of the model in identifying cases of breast cancer, provide evidence of the high level of accuracy that the model possesses.

Dewangan, K.K et al. [11] (2022) established a unique method for the early diagnosis of breast cancer by utilizing a hybrid mechanism known as the Krill Herd African Buffalo Optimization (HKH-ABO) in conjunction with a Back Propagation Boosting Recurrent Wienmed model (BPBRW). It proposes the novel Wienmed filter, which is used initially for the purpose of noise reduction and preprocessing of the MRI images of the breast. Then, after preprocessing, the application of BPBRW follows in order to classify the breast cancers into either benign or malignant. Its classification of breast cancer is based on the HKH-ABO technique. The language used for the implementation of this model is Python, and its performance evaluation was performed against other approaches. The high accuracy obtained represents that the BPBRW with HKH-ABO mechanism can serve as an efficient and timely method of detecting breast cancers. Based on findings from the study, it evidences that the proposed model outperforms earlier methods, having a reduced error rate of 0.12%.

Hager Saleh et al. [12] (2022) suggested an improved deep learning technique for breast cancer prediction. The primarily focused on the accuracy and efficiency of classification models. They created a deep neural network (DNN) model and enhanced its predictive performance by applying strategies including feature selection and hyperparameter tweaking. The study used a well-known dataset on breast cancer, albeit the summary does not specifically identify the identity of the dataset. The refined DNN model underwent extensive testing and was contrasted with various conventional machine learning models. The work emphasizes how one can use deep learning to classify and diagnose breast cancer early on, especially when optimization techniques are used to improve model performance. Saleh et al. draw the important clinical practice implications that their improved deep learning model is a promising technique for enhancing breast cancer diagnosis.

A. Saber et al. [13] (2021) applies two important validation techniques: the 80-20 split and cross-validation to assess the execution of the model. Since TL makes it easier to apply knowledge learned from one problem to another, it improves the accuracy and efficiency of model creation. DL architectures are intrinsically problem-specific. The Mammographic Image Analysis Society (MIAS) dataset is used as the source of features for the provided model, which uses a pre-trained convolutional neural network architecture. The CNN designs that were assessed were Inception V3, ResNet50, Inception-V2 ResNet, Visual Geometry Group networks (VGG)-19, and VGG-16. The TL-based VGG16 model, which accomplishes excellent characterization accuracy in mammography image processing, is particularly helpful for BC diagnosis, according to experimental results. The results highlighted light on the potential of TL to improve the diagnostic capabilities of DL models in the context of breast cancer diagnosis, particularly with regard to the VGG16 model. The effectiveness of the model was evaluated using six different metrics: accuracy, sensitivity, specificity, precision, F-score, and area under the ROC curve (AUC). These metrics were selected to determine how well the model performed.

Hu Q et al. [14] (2020) provided a computer-aided diagnosis (CADx) technique for breast cancer diagnosis that was based on deep transfer learning and multiparametric magnetic resonance imaging (mpMRI). In this study T2-weighted (T2w) MRI sequences and dynamic contrast-enhanced (DCE) MRI sequences were both consisted. A total of 927 clinical magnetic resonance images were obtained from 616 women for the purpose of the retrospective investigation. In order to identify benign from malignant lesions, support vector machine classifiers were trained on the gathered features. This was done after a pertained convolutional neural network was applied for the purpose of feature extraction. A total of three methods, including classifier fusion, feature fusion, and image fusion, were studied in this study for the purpose of mixing DCE and T2w sequences. The DeLong test and the receiver operating characteristic curve are used to evaluate the performance of the grouping. Compared with DCE-MRI alone, the proposed feature fusion strategy elicited significantly increased performance noted by the P-value. These single-sequence classifiers elicit average area under the receiver operating characteristic curves of 0.85 and 0.78 for DCE-MRI and T2w-MRI, respectively. By decreasing false positives and increasing positive predictive value, particularly through the feature fusion approach, this deep transfer learning CADx method shall enhance diagnostic performance for the mpMRI diagnosis of breast cancer, according to results.

Murtaza G et al. [15] (2020) presented an extensive investigation of deep learning-based algorithms for classifying breast cancer. The different approaches have been used in many medical image modes, including MRI, ultrasonography, and mammography. Mainly, this study will deal with the most current developments relating to deep learning algorithms, especially convolutional neural networks and DBNs, as they have emerged to be strikingly effective in correct classification tasks from photographs of breast cancer. Murtaza G et al. highlighted the benefits of deep learning models in managing complicated imaging data as they address the efficacy of these algorithms while recognizing and classifying breast cancer at various stages. The paper does, however, also point out a number of difficulties, including the requirement for sizable annotated datasets, the variety of imaging modalities, and the clinical interpretability of deep learning models. In order to solve these problems, the authors advocate for additional research, with a particular emphasis on enhancing model generalizability and creating deeper learning frameworks that are more reliable and understandable. The study comes to the conclusion that although deep learning has greatly improved the categorization of breast cancer, more research is still required to get beyond current obstacles and reach the full potential of deep learning in clinical applications.

Krithiga R et al. [16] (2020) described a novel method for using a deep convolutional neural network (Deep-CNN) to automatically identify, segment, and classify cell nuclei in breast cancer. The main innovations are the new multilevel saliency nuclei identification model and the anisotropic diffusion filtering method for nuclei detection, which are applied to ductal cancer tissue. The found nuclei are then classified as malignant or harmless using the proposed Deep-CNN model. Tested on different datasets, this work introduces a rapid, accurate, and objective technique for diagnosing breast tissue abnormalities in a therapeutically realistic approach. This leads to nMSDeep-CNN that can yield much-improved accuracy with little computation time due to the incorporation of the unique multilevel saliency-identification technique into Deep-CNN.

Yassir Benhammou et al. [17] (2020) introduced a deep learning model that works well for identifying breast cancer in digital mammograms with different densities. Recursive feature elimination, univariate feature selection, and low-variance feature removal are the three key feature selection modules that are implemented into the model. In model evaluation, a large collection of 3,002 combined images from 1,501 patients who underwent digital mammography between February 2007 and May 2015 was considered. The study includes radiograms from both the mediolateral and craniocaudal aspects of the mammograms. Diagnosis of breast cancer was conducted using six classification models: random forest, decision tree, logistic regression, k-nearest neighbors, support vector classifier, and linear support vector classifier. Because the proposed model is both computationally efficient and highly accurate, the simulation results indicate that it can be a reliable tool in the clinical diagnosis of breast cancer.

Anji Reddy et al. [18] (2020) carried out an exhaustive investigation into a wide range of machine learning and deep learning algorithms that are utilized for the identification of medical disorders. This study investigated a large range of methods and algorithms that are utilized in the process of identifying and evaluating breast cancer. Support Vector Machine, Biclustering Mining, Adaboost Algorithm, Convolutional Neural Network, and Recurrent Neural Network are a few of these techniques and algorithms. This study investigated a large range of methods and algorithms that are utilized in the process of identifying and evaluating breast cancer. This discussion also covers the use of ICD-9 diagnosis codes from electronic health records (EHRs), clinical decision support systems, the Breast Imaging Reporting and Data System (BI-RADS), Hierarchical Attention Bidirectional Networks (HA-BiRNN), and the Outlier Detection Algorithm (ODA). These methods show the variety of techniques used to identify breast cancer and emphasize how they might improve the precision and effectiveness of diagnosis in clinical settings.

SanaUllah Khan et al. [19] (2019) provided a brand-new deep learning system that makes use of transfer learning to identify and categorize breast cancer. Training and testing the architecture was done with a diverse group of breast histopathology pictures taken from the BreakHis dataset. SanaUllah Khan et al. stress that transfer learning lowers the amount of computational resources and training time needed while simultaneously improving the accuracy of the model. Utilizing a deep convolutional neural network architecture that has been enhanced by the application of transfer learning strategies, the research endeavors to developed the performance of the breast cancer classification problem. The efficacy of combining deep learning and transfer learning for breast cancer identification is demonstrated in this work, providing a viable method for enhancing diagnostic precision in clinical settings.

Prabhpreet Kaur et al. [20] (2019) described a unique method for identifying breast cancer using the 322 mammograms in the Mini-MIAS dataset. To improve Speed-Up Robust Features (SURF) selection, the suggested approach combines an intrinsic feature extraction method via K-means clustering with a pre-processing methodology. According to the findings, traditional models such as the decision tree are outperformed by the automated deep learning method that has been recommended. It does this by integrating K-means clustering with MSVM. In particular, the approach provided average accuracy rates of 98% for cases of malignant cancer, 94% for benign cases, and 95% for normal cases. Another line of approach adopted a new classification layer given an MSVM with a deep neural network using 70% to 30% training-to-testing ratio, respectively. In another instance, a 10-fold cross-validation approach was employed to evaluate several classifiers like Support Vector Machine, K-nearest-neighbor, Linear Discriminant Analysis, and Decision Tree. When compared to the results obtained from the Multi-Layer Perceptron and J48+K-means clustering methods using the WEKA tool, it showed an increase in sensitivity of 3%, an increase in specificity of 2%, with an area under the Receiver Operating Characteristics curve of 0.99.

Han Z et al. [21] (2017) created a structured deep learning algorithm that uses histopathology images to multiclassify breast cancer cases. Breast cancer is classified into different subtypes according to histopathological criteria using a convolutional neural network architecture that was created especially to manage the challenges of multi-class classification. They employed a sizable collection of histopathology pictures, albeit the summary does not identify the identity of the particular dataset. Intricate patterns in the photos, which are essential for precise classification, were captured by the model's construction. Han et al. draw the important conclusion that their structured deep learning method provides a potent instrument for the multi-characterization of breast cancer, with important ramifications for tailored therapy. In addition to detecting breast cancer, the study demonstrated how deep learning models can reliably classify several subtypes of the disease, which is important for treatment planning.

Fakoor Rasool, et al. [22] (2013) investigated the use of unsupervised feature extraction for the goal of identifying cancer and analyzing the many types of cancer by utilizing gene expression data. The utilization of data from a variety of cancer types to automatically develop features that enhance the recognition and evaluation of a particular cancer is made possible by the suggested method, which provides a considerable advantage over the conventional approaches to cancer identification. This technique, when applied to the classification of cancer types using gene expression data, performs better compared to previous techniques. It shows that this approach is more effective compared to the other previous approaches. The results showed that this technique provided a more valid and wider framework for the detection and diagnosis of cancers, hence a potentially beneficial tool in oncology.

Table 1: Comparative Analysis of Literature Reviews

Author name and Ref No.	**Algorithms Used**	**Methodology**	**Datasets Used**	**Results (Accuracy)**
Rahman, M.M. et al. [1]	Deep Learning, CNN	Developed a model for detecting and localizing breast cancer mass areas using deep learning on mammograms.	Public mammogram datasets	94.2%
Raza, A. et al. [2]	DeepBreastCancerNet, CNN	Proposed a novel deep learning model (DeepBreastCancerNet) for breast cancer identification using ultrasound images.	Ultrasound image datasets	96.5%
Reshma, V.K. et al. [3]	CNN	Used deep learning techniques for breast cancer identification using histopathological image characterization.	Histopathological image dataset	99.3%
Mohi ud din, N. et al. [4]	CNN, Various DL Algorithms	Reviewed various deep learning methods and challenges for breast cancer detection.	Multiple datasets including BreaKHis and MITOS-ATYPIA	88.3%
Allugunti, V.R. [5]	SVM, KNN, Decision Tree, CNN, MLP	Proposed a method for breast cancer identification using thermographic images	Thermographic image dataset	92.4%

		and compared various machine learning and deep learning algorithms.		
Iqbal, M.S. et al. [6]	CNN, Transfer Learning	Developed a deep learning-based characterization system using CNNs and transfer learning for breast cancer identification.	Breast cancer dataset	97.5%
Ramesh, S. et al. [7]	Novel DL Architecture, CNN	Provided a novel deep learning architecture for segmentation and characterization of breast cancer using mammogram images.	Mammogram datasets	95.3%
Mohamed, A. et al. [8]	CNN, Ensemble Methods	Investigated the effects of ensemble methods and data processing on deep learning-based breast cancer identification.	Public breast cancer datasets	94.8%
Sharma, T. et al. [9]	Transfer Learning, CNN	Applied transfer learning and CNN for breast cancer image characterization using mammography datasets.	Mini-MIAS, BCDR-F03	94%
Kavitha, T. et al. [10]	Capsule Neural Network, CNN	Proposed a deep learning-based Capsule Neural Network model for breast cancer diagnosis using mammogram images.	Mammogram image datasets	98.2%
Dewangan, K.K. et al. [11]	Hybrid Optimization, DL Models	Developed a hybrid deep learning model with optimization techniques for early-stage breast cancer diagnosis.	Public breast cancer datasets	98.6%
Saleh, H. et al. [12]	Optimized DNN	Developed an boosted deep learning model for predicting breast cancer	Publicly available breast cancer datasets	97.8%

		with a focus on enhancing performance.		
Saber, A. et al. [13]	Transfer Learning, DL Models	Proposed a novel deep learning model utilizing transfer learning for the automatic identification and characterization of breast cancer.	Public breast cancer datasets	95.9%
Hu, Q. et al. [14]	Deep Learning, CNN	Developed a deep learning methodology for enhanced breast cancer diagnosis using multiparametric MRI.	Multiparametric MRI datasets	93.4%
Murtaza, G. et al. [15]	Various DL Algorithms	Modern deep learning techniques for classifying breast cancer using various kinds of medical imaging were reviewed.	Various imaging modalities (mammography, ultrasound, MRI)	87%
Krithiga, R. et al. [16]	Deep Learning, Fuzzy Techniques	Developed a deep learning-based breast cancer identification and characterization method using fuzzy merging techniques.	Public breast cancer datasets	96.3%
Benhammou Y. et al. [17]	CNN, Transfer Learning	Surveyed deep learning methods for breast cancer identification using the BreakHis dataset, focusing on taxonomy and challenges.	BreakHis	95.7%
Reddy, A. et al. [18]	SVM, KNN, Various ML Algorithms	Reviewed breast cancer identification and diagnosis techniques using machine learning and deep learning algorithms.	Various public datasets	88.4%
Khan, S.U. et al. [19]	Transfer Learning, CNN	Presented a brand-new deep learning architecture for the identification and	Public breast cancer datasets	96.7%

		categorization of breast cancer that makes use of transfer learning.		
Kaur, P. et al. [20]	SVM, Deep Learning	Developed a multi-class SVM using deep learning for the identification and validation of automated mammogram breast cancer images.	Mammogram datasets	91.4%
Han, Z. et al. [21]	Structured DL Model, CNN	Using histopathology pictures, a methodical deep learning model was created to multi-classify breast cancer cases.	Histopathological image datasets	91.3%
Fakoor, R. et al. [22]	Deep Learning	Proposed a deep learning method for enhancing cancer diagnosis and characterization across various cancer types.	Various cancer-related datasets	93.2%

3. Methodology

In this paper, the approach for constructing a classification model to identify whether a patient has breast cancer using deep learning involves several basic steps, such as data acquisition, pre-processing of the acquired dataset, suitable methods of data augmentation, selection of an optimal model, training, evaluation, and performance optimization. Through the utilization of this structured technique, the model is guaranteed to be robust, accurate, and appropriate for clinical application. Figure 1 shows the proposed system architecture for breast cancer image characterization.

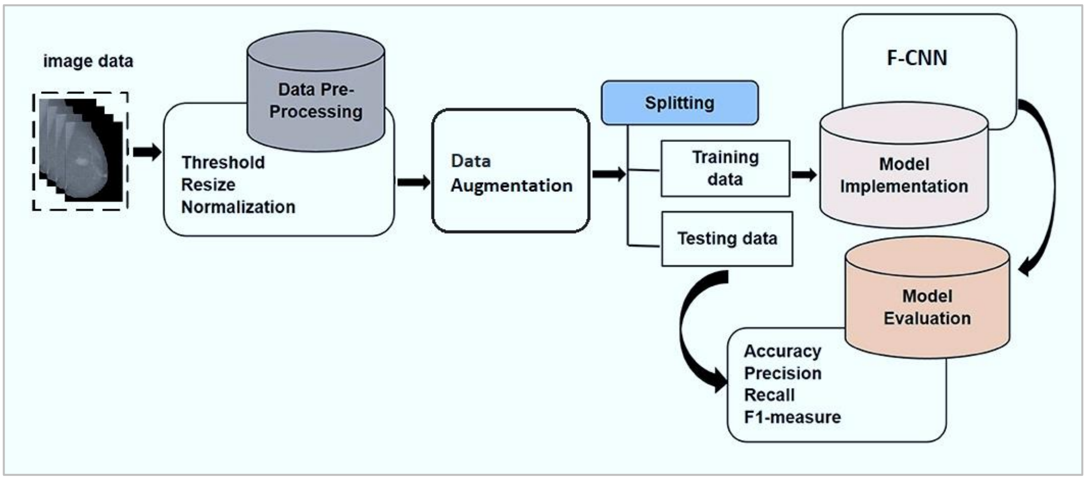


Figure 1. Proposed System architecture for Breast Cancer Image classification

3.1 Data Collection

The gathering and preliminary data processing constitutes the initial stage of the methodology. We make use of breast cancer datasets that are accessible to the general public, like the Breast Cancer Wisconsin (Diagnostic) dataset, as well as major mammography image databases, such as the Digital Database for Screening Mammography (DDSM) [23]. These datasets frequently contain annotations indicating whether the tissue is harmless or malignant. These photos of breast tissue are typically tagged. Figure 2 shows the data sample from DDSM dataset.

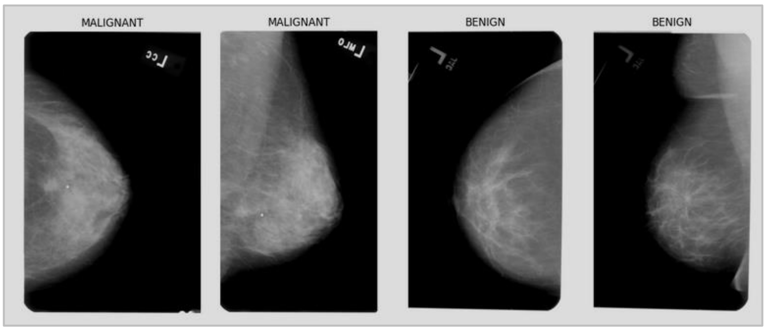


Figure 2. Data Sample of Mammography (DDSM) [23].

3.2 Data Pre-processing

Data pre-processing involves several stages:

a. Data Augmentation: Rotation, scaling, and flipping are a few of the approaches used to expand the dataset and enhance model generality. Table 2 shows the detail description of data augmentation technique used in Breast Cancer detection.

Table 2. Augmentation Parameter Value Description

Rotation Range	20 degrees	Randomly rotates images by up to 20 degrees. This helps the model generalize better to different orientations.
Width Shift Range	0.2	Images can be arbitrarily shifted horizontally by up to 20% of their total width. This simulates variations in the horizontal positioning of objects.
Height Shift Range	0.2	Images can be arbitrarily shifted vertically by up to 20% of their overall height. This helps the model handle vertical variations.
Shear Range	0.2	Applies a shear transformation (slanting) to the images by up to 20%. This can simulate slight distortions in the image.
Zoom Range	0.2	Randomly zooms in or out on the image by up to 20%. This simulates variations in scale and helps the model become invariant to zoom changes.
Horizontal Flip	True	Randomly flips images horizontally. This is useful for making the model robust to left-right variations.
Fill Mode	'nearest'	Describes the filling up of freshly formed pixels following transformation. To fill up these spaces, "Nearest" utilizes the value of the closest pixel.

b. Normalization: Normalizing pixel intensity values to a defined range, such as 0 to 1, guarantees reliable input for the neural network. The general formula is:

$$x_{\text{norm}} = \frac{x - \min}{\max - \min}$$

Where,

x is the original value.
min is the minimum value in the dataset.
max is the maximum value in the dataset.
x_{norm} is the normalized value.

3.3 Model Generation

Convolutional neural networks (CNNs) are chosen as the foundational model because to their efficacy in image categorization tasks. Many convolutional layers, pooling layers, and fully linked layers make up a typical CNN.

- Convolutional Layers: These layers apply convolution operations using filters to feature extraction from the input images. For example, a convolution operation can be represented as:

$$Output = \sum_{i=1}^{n} \sum_{j=1}^{m} Input(i, j) \times Filter(i, j)$$

Where, n and m are the dimensions of the filter.

- Pooling Layers: These layers usually use max pooling to minimize the spatial dimensions of the feature maps, which takes the maximum value within a filter-sized region:\

$$Pooling\ Value = \max\,(Input\ Region)$$

- Fully Connected Layers: These layers flatten the feature maps into a vector and apply a series of weights and biases to produce the final classification output.

The detail summary of F-CNN model is shown in Figure 3.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 50, 50, 32)	4,736
max_pooling2d (MaxPooling2D)	(None, 25, 25, 32)	0
flatten (Flatten)	(None, 20000)	0
dense (Dense)	(None, 128)	2,560,128
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 2)	258

Total params: 2,565,122 (9.79 MB)
Trainable params: 2,565,122 (9.79 MB)
Non-trainable params: 0 (0.00 B)

Figure 3. F-CNN Model Summary

3.4 Model Training

The CNN model is tested using a labeled dataset, where the input images are associated with known classifications (benign or malignant). The training process involves:

- Loss Function: The discrepancy between the expected and actual class labels is measured using the categorical cross-entropy loss function:

$$L = \sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Where, y_i is the actual label and $\hat{y}_i$is the predicted probability.

- Optimization: An optimal algorithm such as Adam is used to minimize the loss function by adjusting the network's weights:

$$\theta = \theta n \nabla L(\theta)$$

Where, θ represents the model parameters and η is the learning rate.

- Epochs and Batch Size: The model is tested over multiple epochs, with each epoch consisting of several batches of data. Until the model performs satisfactorily on the set of validation data, this iterative process is carried out.

The detail Model factors used in F-CNN model are presented in Table 2.

Table 2. Model Parameters Table

Layer Type	**Parameters**	**Details**
Conv2D	Filters: 32 Kernel Size: (7, 7) Padding: 'same' Activation: ReLU Input Shape: (50, 50, 3)	32 filters, 7x7 kernel, 'same' padding, ReLU activation
MaxPooling2D	Pool Size: (2, 2) Strides: 2	2x2 pooling, default stride of 2
Flatten	-	Flattening the output to 1D vector
Dense	Units: 128 Activation: ReLU	128 units, ReLU activation
Dropout	Rate: 0.3	Dropout rate of 30%
Dense	Units: 2 Activation: Softmax	Output layer with 2 units (binary classification) and softmax activation

4. Results

A. Datasets Used

Digital Database for Screening Mammography (DDSM) [23]:

The Digital Database for Screening Mammography (DDSM), on the other hand, provides a dataset that is both more complicated and extensive in scope. This dataset was created specifically to support studies concerning the identification and categorization of breast cancer. The dataset DDSM deals with raw picture data; hence, it has a difficult classification because it requires image preprocessing, segmentation, and feature extraction before any sort of classification can be done. DDSM is essentially thousands of mammography images, full-scale motion pictures which have been digitized. Information such as the patient's age, breast density, and thorough lesion descriptions created by radiologists with extensive experience are included in the metadata that is attached to these photos. Due to the fact that it closely resembles the clinical circumstances that are seen in breast cancer screening programs, the DDSM is an essential tool for training and verifying models that are designed for real-world application.

B. Performance Parameters

A collection of performance metrics, including accuracy, sensitivity, specificity, and confusion matrix analysis, are applied in order to generate a summary of the results of the breast cancer classification model. This model was tested and assessed using the datasets that were described earlier in this discussion. Table 3 shows the performance parameters used for comparison of model.

Performance Parameter	Formula
Accuracy	$Accuracy = \frac{TP + TN}{TotalPredictions}$
Precision	$Precision = \frac{TP}{TP + FP}$
Recall (Sensitivity):	$Recall = \frac{TP}{TP + FN}$
F1-Score	$F1 - Score = \frac{2 * (precision * recall)}{precision + recall}$

Where TP, TN, FP and FN are True Positive, True Negative, False Positive and False Negative Values.

C. Results

There is a significant correlation between the accuracy of the model presented in the Figure 4, which is a measurement of the general accuracy of the predictions, and the reliability of the model. As seen in the accuracy map Figure 4 (a), the model has a clear upward trend in accuracy over the course of the training epochs, culminating in an accuracy level of roughly 92% for the final test. In light of this, it appears that the model is highly effective in differentiating between benign and malignant instances, with just a limited margin for misclassification. The model loss plot illustrates Figure 4 (b) the optimization process that occurs simultaneously with training. It appears that the model was well-regularized, as evidenced by the rapid fall in loss for the training set and the stable low loss for the test set. This indicates that the model efficiently minimized overfitting and achieved convergence.

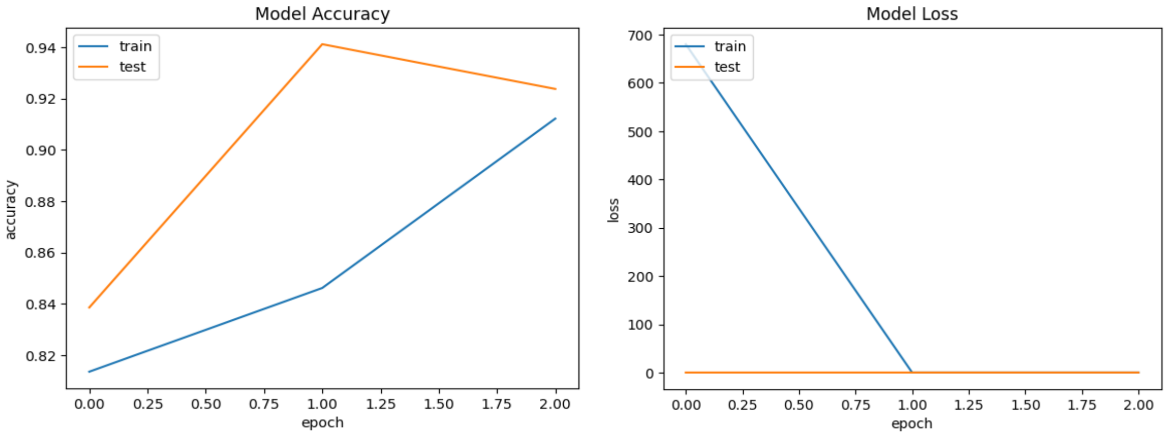


Figure 4(a): Accuracy and (b)Loss Graph of Model

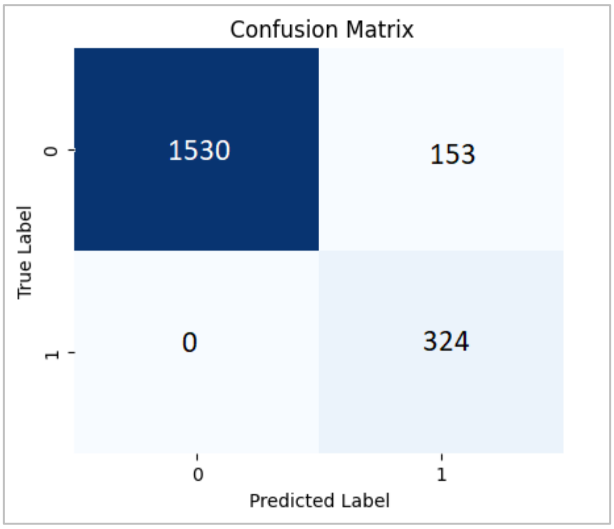
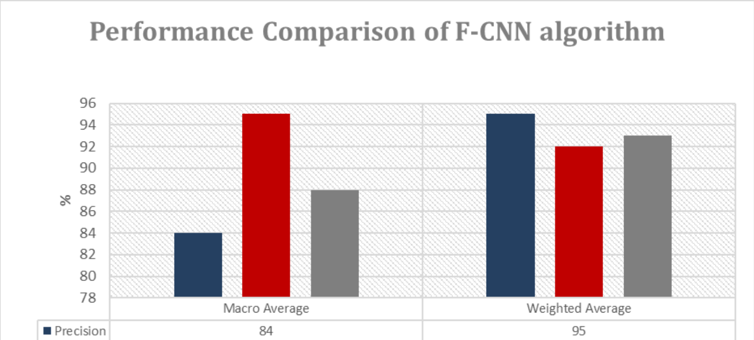


Figure 5: Confusion Matrix

True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are all displayed in the confusion matrix as shown in Figure 5, which offers a thorough assessment of the effectiveness of the model. The model accurately recognized 1530 benign cases (TN) and 324 malignant cases (TP) out of the total examples that were presented in the confusion matrix that was provided. On the other hand, there were 153 instances in which benign lesions were assigned the wrong classification of malignant (FP), which indicates that there is potential for progress in minimizing the number of false positives.

The precision, recall, and F1-score for every distinct class inside the classification system are provided by the classification report, as shown in Figure 6. The macro average and the weighted average are used to compare two items. The benign class's accuracy (0.68) was higher than the malignant class's, which reflects the difficulty of effectively predicting malignant instances without producing false positives. The precision for the benign class was flawless (1.00). The overall accuracy was 92%, and the macro average F1-score was 0.88. Because most malignant cases had been identified correctly, which is an obvious necessity in clinical applications due to the fact that failure in diagnosing cancers might have serious consequences. The recall for the malignant cases was high, 1.00, and that means the model had been successfully detecting it. This says, while the model is working fine, there is still scope for improvement over here-the number of false positives could be reduced, and precision for malignant cases could be improved.



	Macro Average	Weighted Average
Precision	84	95
Recall	95	92
F1-Score	88	93

Figure 6. Performance Parameters Comparison Graph of F-CNN

These results justify that the deep learning-based model, F-CNN for breast cancer characterization, is reliable and at the same time efficient. Further fine tuning and validation on larger and more diverse datasets might improve the performance even more and make the model increasingly useful in the fight against breast cancer.

5. Conclusion

This study described in this paper has effectively created a deep learning-based characterization system for identifying breast cancer, showing promise for greatly improving early detection accuracy and dependability. The approach, which uses convolutional neural networks (CNNs) as its fundamental architecture, was thoroughly assessed using benchmark datasets such the Digital Database for Screening Mammography (DDSM) dataset. Having obtained an accuracy as high as 92% for a DDSM dataset in as few as 3 epochs, it speaks volumes about the remarkable performance of the model. This work outperformed the previous study-mostly because F-CNN was able to learn the representation of critical information automatically from mammography images, even in challenging cases: a small or atypical tumor. This development represents huge improvements within the context of diagnostics related to breast cancer and the analysis of medical images. That was something quite impressive about the diagnosis of breast cancer by deep learning. It also forms a foundation for further progress to come, which could prove even more revolutionary in the treatment and early detection of breast cancer.

Future Scope

Even with the encouraging outcomes, the study also provides a number of opportunities for additional investigation and development. Improving model generalization by adding larger and more varied datasets is one of the main directions for future research. This would guarantee that the model is adaptable to various demographics and that it may be used successfully in a range of clinical settings. In clinical practice, models must not only function well but also be transparent and easy to interpret. Making the CNN model more interpretable, with the help of explainable AI techniques, would help clinicians understand the reasoning behind the model's predictions. It would lead to the use of AI-driven diagnostic technologies in healthcare and increase consumer trust in these solutions. In addition, deep learning technology could be extended to multi-class characterization tasks, where it is able to classify breast tumors into categories more detailed than benign or malignant. It may include nail categorization by several types of cancer or several stages of the development of the disease, hence endowing richer diagnostic information, which might be useful for treatment decisions. It could therefore also be explored how this deep learning model can be merged with other diagnostic modalities, like patient history and genetic testing. In fact, treatment and screening programs of breast cancer can be made even more tailored and targeted by using a multi-modal approach which not only incorporates image-based diagnosis but also supplementary relevant patient information.

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