International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.1 (2025) pp. 261-273
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

BCDNet: Using Mammogram Images to Detect Breast Cancer with an Improved Convolutional Neural Network

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Article Info:

DOI: 10.22399/ijcesen.811
Received : 24 October 2024
Accepted : 31 December 2024

Keywords :

Convolutional neural networks,
artificial intelligence,
deep learning,
enhanced CNN,
breast cancer screening.

Abstract:

AbstracAmong the world's leading causes of death for women is breast cancer. Significant progress has been made in the diagnosis of breast cancer since the advent of artificial intelligence (AI). In order to cure breast cancer and make informed treatment decisions, early identification is essential. Deep learning (DL) techniques are frequently utilized in computer vision, but they have also been applied in a number of other sectors, including medicine. A well-liked paradigm for medical image analysis
but its performance may not be optimal for a specific imaging modality without empirical study. This paper introduces an enhanced CNN model called Breast Cancer Detection Network (BCDNet), designed to be more efficient with breast mammogram images. We also propose an algorithm called Learning-Based Cancer Screening (LBCS) that leverages the BCDNet model. An empirical study using the CBID-DDSM benchmark dataset demonstrates that BCDNet attains the best level of accuracy of 97.68%, outperforming many of the deep learning models in use today. Medical facilities can use this proposed model as part of a CDSS for breast cancer screening.

1. Introduction

Lung cancer was the top cause of death for males and the third most common cause of death for women, per a 2018 database created by the International Agency for Research on Cancer (IARC) Global Cancer Observatory. The database contained data on 185 different countries' incidence and mortality rates for 36 distinct cancer forms.

There were about 9.6 million cancer-related fatalities recorded in 2018; of these, around 1.8 million deaths, or 18.4% of all deaths, were attributable to lung cancer [1]. Due to the extremely high incidence of lung cancer and the concerning rise in mortality from the disease in the natural world, early detection techniques, different cancer control studies, and research have been implemented to reduce mortality. Curing lung cancer usually requires early illness identification, and lower lung cancer incidence rates are the consequence of good diagnosis techniques. Currently, there are seven methods available for treating lung cancer: computed tomography (CT) scans, magnetic resonance imaging (MRI), positron emission tomography (PET), breath analysis, and cytology sputum [2]. Every lung cancer screening method now in use has a particular threshold for detection and a range of indicators. Additionally, these methods have certain disadvantages. In contrast to MRI and PET, which are less successful in identifying and staging lung cancer, CT, Septum, and CXR are radiation-prone. Serum testing is also an intrusive method whose sensitivity and specificity are insufficient for early detection, which makes the results unacceptable. However, sputum has the ability to identify lung cancer early on because
gene promoter methylation but further research was necessary. Furthermore, compared to CXR, which has a large proportion of false negative readings and poor sensitivity, More research samples were needed even though the VOC in urine demonstrated good sensitivity and specificity. The most efficient way to find lung cancer these days is by computed

tomography (CT) imaging, which gives exact details on the nodular sizes and places. The low-dose CT examination enabled early cancer identification of the tumors. It resulted in a 20.0% decrease in mortality as well as a notable rise in the number of positive screening test results in contrast to conventional radiography techniques. Histopathological samples and genome sequencing types are widely used in lung cancer research. Many contributions are found in the literature focusing on deep learning models for automatically detecting lung cancer. The literature has noted that the CNN model is widely used and efficient for medical image analysis. However, since one size does not fit all, it cannot provide optimal performance with all imaging modalities and problems. Therefore, enhancing the CNN model to achieve optimal performance in detecting breast cancer using mammogram images is important.

In our paper, we present two main contributions. Firstly, we introduce a refined CNN model called the Breast Cancer Detection Network (BCDNet), specifically designed to analyze breast mammogram images efficiently. We propose an algorithm called Learning-Based Cancer Screening (LBCS), which utilizes the BCDNet model. Our empirical study, conducted using the CBID-DDSM benchmark dataset, demonstrates that BCDNet outperforms many existing deep learning models, attaining a remarkable 97.68% accuracy rate. This model may be used as part of a Clinical Decision Support System (CDSS) for breast cancer screening at medical institutions. This is how the remainder of the paper is structured: In Section 2, prior research on deep learning models for breast cancer detection is reviewed. In Section 3, an outline of deep learning, specifically the CNN model. Section 4 introduces the methodology for automatically detecting breast cancer to improve the state of the art at the moment. Experiments and our empirical study are presented in Section 5. Our work is summarized in Section 6 along with recommendations for further investigation.

2. Related work

Using mammography pictures as an imaging modality, numerous researchers helped to automatically diagnose breast cancer. [1] Abdelrahman et al.

examined CNN uses in mammography, outlining future research prospects and talking about tasks, datasets, and practical implementations. Sereshkeh et al. [2] looked at predicting tumor stage and lymph node involvement in patients with breast cancer by using deep characteristics from mammography. Islam et al. [3] exceeded previous models in the identification of breast cancer by introducing an Ensemble Deep Convolutional Neural Network (EDCNN) model. Singh et al. [4] for the effective identification of suspicious mass in digital mammograms, pixel-based pre-processing and Faster R-CNN are used in an efficient hybrid technique. Karthiga et al. [5] increased by early identification of breast cancer. This is aided by mammography facilitated by AI. Models of hybrid deep neural networks function well.

Koshy et al. [6] identified breast cancer is essential. Diagnoses are aided by the effective classification of histological pictures using LMHistNet, a deep neural network. Anas et al. [7] improved by recent AI developments, most notably deep learning. Accuracy is increased by decreasing False Positive and Negative Rates using the YOLOv5 and Mask R-CNN models. Wen et al. [8] used a variety of imaging techniques, AI-enabled computer-aided diagnosis of breast cancer is beneficial for early detection, which is critical for survival. Techniques from deep learning and machine learning are compared. Shah et al. [9] for breast cancer to be effectively treated, early diagnosis is essential. Mammography is important, however the trustworthiness of synthetic pictures has to be increased. Tan et al. [10] improved the identification of tiny masses, RCM-YOLO, a novel breast mass detection network, lowers the number of missed and incorrect diagnoses.

Torabi et al. [11] used adversarial and self-supervised learning strategies to address breast cancer detection problems, greatly increasing accuracy and flexibility. Sani et al. [12] presented a unique CNN framework that improves the efficiency and accuracy of breast cancer classification by leveraging group theory and DCT. Loizidou et al. [13] highlighted CAD systems and potential areas for future development while focusing on the application of mammography in the diagnosis of breast cancer. Asadi et al. [14] for breast abnormalities to be effectively treated, early diagnosis is essential. High diagnostic accuracy is attained via a cascade network model that combines segmentation and classification. Atrey et al. [15] improved the accuracy of breast cancer diagnosis, a hybrid deep learning bimodal CAD algorithm integrates ultrasound and mammography images. The proposed model performs significantly better with an accuracy of unimodal systems and presents opportunities for future research and clinical advantages.

Gami et al. [16] widespread malignancy that kills a lot of people worldwide. Early identification and therapy are facilitated by computer-aided detection methods that use deep learning to diagnose malignant cells with high accuracy. Frank [17] for breast mass localization on mammograms, an integrated deep learning system integrates CNN and YOLO v5 object identification, facilitating effective physician evaluation. Saran et al. [18] predicted by breast density. Density classification accuracy for screening is improved using a deep learning classifier that uses transfer learning. Mohapatra et al. [19] compared to traditional CAD systems is deep learning-based breast cancer diagnosis. We test a variety of CNN architectures, proving that transfer learning is effective: AlexNet, VGG16, and ResNet50. Mechria et al. [20] investigates the relationship between a Deep Convolutional Neural Network's (DCNN) breast cancer detection ability and the quality of the mammography pictures. When compared to Wiener and median filters, denoising using DCNN dramatically increases classification accuracy, specificity, and sensitivity.

Petrini et al. [21] highlighted how well deep convolutional neural networks function for diagnosing breast cancer from mammograms. Three transfer learnings are employed in a unique way to build a high-performance CAD system that significantly outperforms single-view classifiers. The model and code for this method are publicly available. Aljuaid et al. [22] classified breast cancer accurately using deep neural networks and transfer learning on the BreakHis dataset. The most successful model is ResNet. Increasing accuracy and expanding the dataset are among the next plans. Omonigho et al. [23] increased the tumor detection accuracy of the system. Outperforming conventional techniques, modified AlexNet DCNN classifies mammography pictures into benign and malignant cancers with huge accuracy. Agnes et al. [24] increased by early detection of breast cancer. With 96% sensitivity and 0.99 AUC, the mammogram-specific MA-CNN was designed to effectively classify pictures and support diagnosis. Shakeel and Raja [25] used a tailored DCNN architecture, a revolutionary CAD approach achieves an accuracy in classifying breast cancer as malignant or benign.

Yurttakal et al. [26] important to diagnose breast cancer early. Early detection is aided by mammography; however, MRI provides better soft tissue imaging. High accuracy is attained with a CNN-based method, which helps with diagnosis. Chouhan et al. [27] saved by early identification of breast cancer. A DFeBCD system with a variety of features—including dynamic ones—performs better than one with only one feature. Ekici et al. [28] approached detecting breast cancer is thermography, which is non-invasive. It may even outperform mammography in terms of price and convenience of use for screening. Hassan et al. [29] presented a deep convolutional neural network-based classification model for breast cancer masses that has excellent accuracy rates. Nagpure et al. [30] with 1 in 28 Indian women at risk, breast cancer poses a serious threat to them. Early detection with neural networks and data mining helps with prompt therapy.

Djebbar et al. [31] updated CAD method that makes use of YOLOv3 aids in the identification and categorization of mammography masses, offering practical and reliable outcomes. Kavitha et al. [32] used a variety of methods, the OMLTS-DLCN model diagnoses breast cancer with good accuracy on benchmark datasets. Patil et al. [33] suggested using deep learning, tumor segmentation, and image pre-processing to create a hybrid classifier for mammography-based breast cancer diagnosis. Shu et al. [34] suggested to use unique pooling structures for lesion identification in a deep learning-based mammography classification technique that produced competitive results. Salama et al. [35] identified breast cancer with high accuracy and efficiency, a novel framework makes use of many deep learning models.

Sun et al. [36] for the categorization of mammogram images, a unique approach combines multi-view CNNs with modified loss functions and outperforms state-of-the-art techniques. Isaza et al. [37] compared to current methods, great accuracy was obtained in the segmentation and classification of breast lesions using DL structures. Songsaeng et al. [38] with high accuracy and high AUROC, multi-scale designs improve the ability of radiologists to identify breast calcification in mammography. Khan et al. [39] for a better prognosis, breast cancer identification must occur early. Accurate categorization is improved by the multi-view CADx system, which uses four mammography scans. Meenalochini and Kumar [40] assisted in the early diagnosis of breast cancer, mammography lowers death rates. This study examines feature extraction, segmentation, and pre-processing methods in machine learning for categorization. It has been noted in the literature that the CNN model is widely used and efficient for medical image analysis. However, since one size does not fit all, it cannot provide optimal performance with all imaging modalities and problems. Therefore, it is important to enhance the CNN model to achieve optimal performance in detecting breast cancer using mammogram images.

An example of an artificial neural network is frequently used for processing and classifying images is the convolution neural network, which is specifically made to handle pixel data. CNN's architecture has the advantage of reducing the image in a way that preserves its features and makes it easier to analyze because it consists of multiple layers that are absent from the standard neural network [9]. Artificial neurons comprise these layers. In the different layers that are available, neurons are in charge of extracting features. Pixel patches of a picture are fed to the neurons when it is designated as a CNN model participation; the neurons then identify features in the image. The first layer identifies the image's fundamental characteristics, like size and orientation. As the layer number rises, more advanced features are taken from the output that has been acquired and sent to a higher layer. The CNN architecture is depicted in the figures in ref [10]. The convolution layer performs convolution, This is the mathematical process of creating a new signal by combining two signals. A kernel is applied to each pixel in the image during image processing, producing a single-dimensional value for that specific field of reception. Researchers can then use the reduced image to extract features.

In terms of the pooling layer, it carries out actions to reduce the input/extracted feature array's dimensions, which lowers the computational cost [11]. There are two varieties of it: maximum pooling and average pooling. A kernel is applied to the input, much like in convolution, and a single value is extracted for that specific input portion. The value will be obtained based on the type of pooling. By inserting the kernel one at a time into each segment, max pooling yields the single value output for the highest value in the area where the input and kernel overlap. This process is repeated for all the input segments. The overlapped input and kernel portion values will be averaged for average pooling.

Additionally, the input noise is reduced by the pooling layer. The classification's ultimate output will come from the final completely connected layer, which gives the probability value indicating the number of connected neurons in the hidden layers. Non-linear inputs are easily classified by this fully connected layer. Before the fully linked layer receives its input, the flatten layer immediately before it flattens it into a one-dimensional array. Iterations spanning multiple epochs for training purposes. Updating the weight and bias on a regular basis guarantees ideal model tuning. Different activation functions that take weight and bias as inputs and produce an output are available.

3. Materials and Procedures

The suggested deep learning framework for breast cancer automatic detection is presented in this part. It includes the description of the improved CNN model, the architecture of the suggested framework, the problem specification, dataset details, the algorithm, and the evaluation methodology.

3.1 Problem Definition

Provided a breast cancer mammography image of a person, developing The difficult problem under consideration is the use of a deep learning-based system for the efficient and automated diagnosis of breast cancer probability.

3.2 Our Framework

We have created an efficient system for detecting breast cancer from mammography images using deep learning. Our empirical investigation made use of The CBIS-DDSM dataset is commonly utilized in research on the diagnosis of breast cancer. The framework allows the system to learn during training and then detect breast cancer in testing. We preprocessed the given dataset to increase test sample diversity and raise the standard of the training procedure. The data was divided into test and training sets following preprocessing. 80% of the samples in this study were allocated to the training set, and 20% to the testing set. BCDNet, the suggested improved CNN model, is trained utilizing labeled data from training examples in order to acquire expertise. Following training, the model is saved or persisted in secondary storage. This is done to ensure that the system can continue functioning and screen new patients for breast cancer diagnosis using the trained model. The saved model is reused in the system when needed. When new training samples are received, the system retrains Transfer lear ning is being used by the model to enhance its performance. The saved model is loaded when required to test whether a mammography sample shows any probability of breast cancer. This process is known as testing. The model is evaluated using a specified methodology, which provides performance metrics reflecting how well the model was trained and used in the suggested structure. Figure 1 shows the overall suggested framework.

3.3 Proposed Enhanced CNN Model

The augmented CNN model that has been proposed, as presented in Figure 2, is known as a Breast Cancer Detection Network (BCDNet). It is implemented using TensorFlow's Keras API to detect breast cancer efficiently. The model begins with'same' padding, a 3x3 kernel, 32 filters, and a ReLU activation function in the convolutional

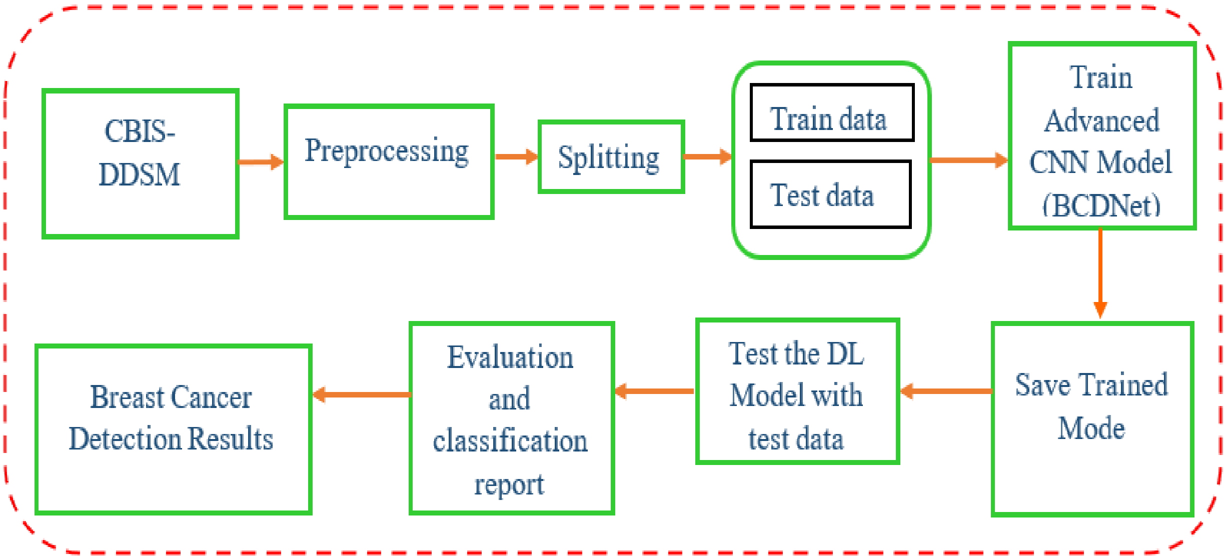

Figure 1. *Deep learning framework for automatic breast cancer diagnosis*

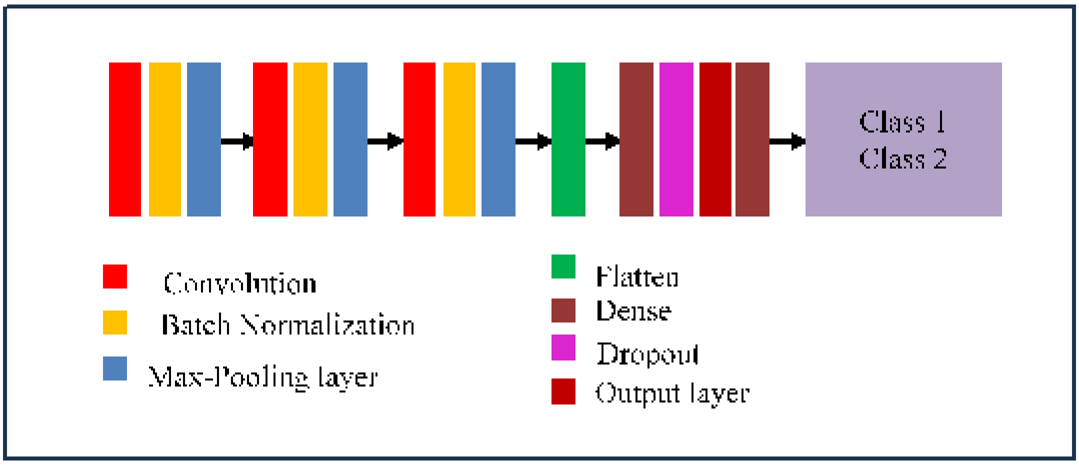

Figure 2. *Architecture of the proposed enhanced CNN model known as BCDNet*

layer. A max-pooling layer with a default stride and a 2x2 pool size comes next, followed by a batch normalization layer. Subsequently, Using the corresponding batch normalization and max-pooling layers,'same' padding, ReLU activation, and two more 64- and 128-filter convolutional layers are added. The final convolutional layer uses ReLU activation, 128 filters, and "same" padding. Next, a 3x3 pool size and stride of two are used for batch normalization and max-pooling. The model then flattens the output before moving on to a fully linked layer that has 128 units, a dropout layer with a rate of 0.3, and ReLU activation. The last output layer of the model uses the softmax activation function, which has two units for binary classification.In essence, the enhanced CNN model is constructed in a step-by-step fashion, starting with convolutionalmax-pooling to reduce the spatial dimensions of the convolved features after layers to extract features from the input image data and batch normalization to increase training speed and stability. The model then flattens the output and transitions to fully connected layers for classification, incorporating dropout to prevent overfitting. Figure 3 shows layers and configuration details of the BCDNet. The output layer's use of softmax activation suggests that the model is intended for binary classification tasks, in which it determines the chance that an input belongs to each class and chooses the one with the highest

Layer	Convolution	Max pooling
First layer	filters=32	pool_size=(2,2)
	kernel_size=(3,3)	strides=(2)
	padding="same"	
	activation=ReLU	
Second layer	filters=64	pool_size=(3,3)
	kernel_size=(3,3)	strides=2
	padding="same"	
	activation="ReLU"	
Third layer	filters=128	pool_size=(3,3)
	kernel_size=(3,3)	strides=2
	padding="same"	
	activation="ReLU"	
Forth layer	filters=128	pool_size=(3,3)
	kernel_size=(3,3)	strides=2
	padding="same"	
	activation="ReLU"	
Parameter	**Value**	
Batch size	25	
learning rate	75	
optimizer	adam	
no of epochs	25	
total parameters	3,08,162	
trainable parameters	3,07,458	
non-trainable parameters	704	

Figure 3. *Layers and configuration details of the BCDN*et

likelihood. Overall, this construction demonstrates a comprehensive approach to building an convolutional, batch normalization, An enhanced convolutional neural network (CNN) for breast cancer diagnosis must have max-pooling, fully connected layers, appropriate activation functions, and dropout regularization to boost the model's performance and generalization skills . This systematic configuration aligns with best practices in CNN design and showcases a foundational implementation for deep learning problems related to breast cancer detection.

3.4 The proposed algorithm

We propose an algorithm called Learning-Based Cancer Screening (LBCS) that utilizes the BCDNet model based on an empirical study using the CBID-DDSM benchmark dataset. Using the CBIS-DDSM dataset, our system, LbBCD, seeks to identify breast cancer. The process begins with data modeling, where the dataset D undergoes a preprocessing step to derive D'. The algorithm then involves data preparation, model building, and training. The BCDNet model is configured as depicted in Figure 2, compiled,

Algorithm: Learning-based Breast Cancer Detection (LbBCD)
Input: CBIS-DDSM dataset D
Output: Breast cancer detection results R, performance statistics P

1. Begin
   Data Modelling
2. D'←DataPreProcess(D)
3. (T1, T2)←DataPreparation(D')
   Model Building and Training
4. Configure BCDNet model m as in Figure 2
5. Compile m
6. m'←TrainBCDNet(T1)
7. Persist m'
8. Load m'
   Breast Cancer Detection
9. R←CancerDetection(T2, m')
   Performance Evaluation
10. Generate confusion matrix
11. P←Evaluate(R, ground truth)
    Display Output
12. Print R
13. Print P
14. End

Algorithm 1: *Learning-based Breast Cancer Detection (LbBCD)*

and then trained using the preprocessed data D'. The trained model m' is persisted and loaded for the breast cancer detection phase. During this phase, the algorithm detects breast cancer using the prepared data T2 and the loaded model m', resulting in the output R. The performance evaluation entails generating a confusion matrix and evaluating the results R with the ground truth to obtain performance statistics P. The final step involves displaying the output by printing the results R and performance statistics P. Among the crucial processes of the LbBCD technique are data preprocessing, model construction, and training, breast cancer detection, and performance evaluation. The algorithm aims to effectively process the CBIS-DDSM dataset to detect breast cancer and provide performance statistics. This structured approach ensures the systematic utilization of the dataset and the trained model to achieve accurate and reliable breast cancer detection results.

Overall, this algorithm highlights the significance of data processing while offering a thorough framework for breast cancer identification, model training, and performance evaluation. By following a systematic flow, from data preparation to result display, the LbBCD algorithm aims to advance breast cancer detection using machine learning techniques, potentially offering valuable insights for medical professionals and researchers.

3.5 Dataset Details

One popular benchmark is the DDSM Curated Breast Imaging Subset (CBIS-DDSM) dataset. for mammography screening. It contains 2620 mammography samples, including Information about normal, benign, and malignant instances as well as related pathologies. This dataset is essential for supervised learning processes, providing ground truth. The images in the dataset have Breast cancer diagnosis after being decompressed and converted to DICOM format requires feature-enhanced ROI segmentation and bounding boxes.

3.6 Evaluation Methodology

Since we used a learning-based approach, metrics are utilized to assess our methods and are obtained from the confusion matrix, as illustrated in Figure 4.

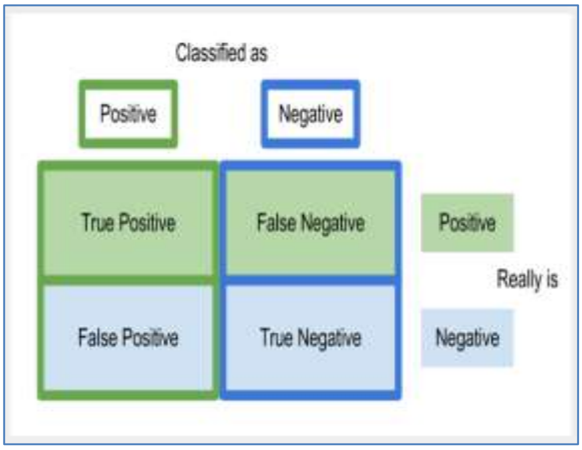

Figure 4. *Confusion matrix*

Our method's predicted labels are compared using ground truth to calculate performance statistics based on the confusion matrix. The measures utilized in the performance evaluation are expressed by Equations 1 through 4.

$$\text{Precision } (p) = TP/(TP+FP) \quad (1)$$
$$\text{Recall } (r) = TP/(TP+FN) \quad (2)$$
$$\text{F1-score}=2*((p*r))/((p+r)) \quad (3)$$
$$\text{Accuracy}=(TP+TN)/(TP+TN+FP+FN) \quad (4)$$

A value between 0 and 1 is the outcome of the performance evaluation metrics. Machine learning research makes extensive use of these metrics.

4. Experimental results

This section displays the experimental findings of our empirical investigation, which was conducted using a prototype application designed to automatically detect breast cancer from mammography images. A number of cutting-edge tip learning models, such baseline CNN, LeNet, and UNet, are compared to the suggested deep learning model, BCD net, in order to assess its performance. The observations include exploratory data analysis which analyses the data distribution dynamics and results of breast cancer screening. Experiments are done with a benchmark data set known as CBIS-DDSM, which contains breast mammography images. As presented in Figure 5, the crapped version of the breast mammogram image is provided as part of exploratory data analysis. As presented in Figure 6, the full breast mammogram image is provided. The full mammogram image is the one which is not cropped. As presented in Figure 7, it is observed that an ROI mask is provided associated with a breast mammogram image useful as ground truth to validate the performance of breast cancer prediction. As presented in Figure 8, it is observed that the total number of patients available in the dataset is divided into two categories: healthy and breast cancer-affected. As presented in Figure 9, the data set contains three kinds of images: cropped, full mammogram, and ROI mask images. It shows the distribution of the three kinds of data in the given dataset.

As presented in Figure 10, the total number of breast mammography samples in the data set, along with the left breast count and right breast count, are visualized. As presented in Figure 11, the data set contains two kinds of abnormalities: calcification and mass abnormalities. The data distribution of these two abnormalities is visualized. As shown in Figure 12, the data distribution dynamics of left and right breast mammography images related to

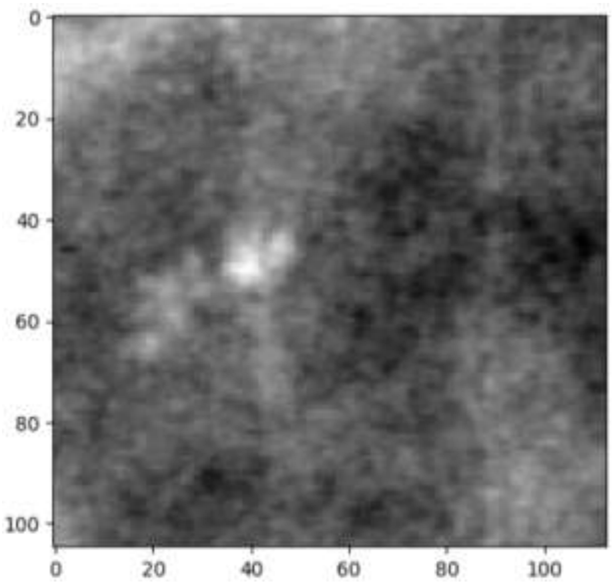

Figure 5. *Cropped mammogram image*

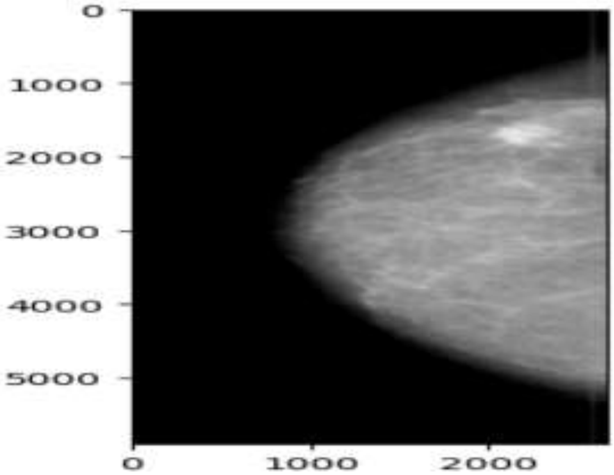

Figure 6. *Shows full mammogram image*

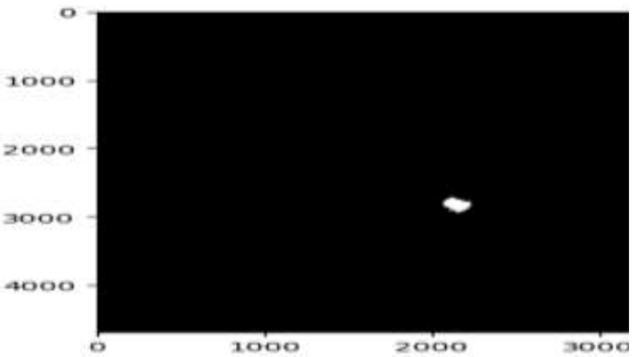

Figure 7. *ROI mask of a breast mammogram image*

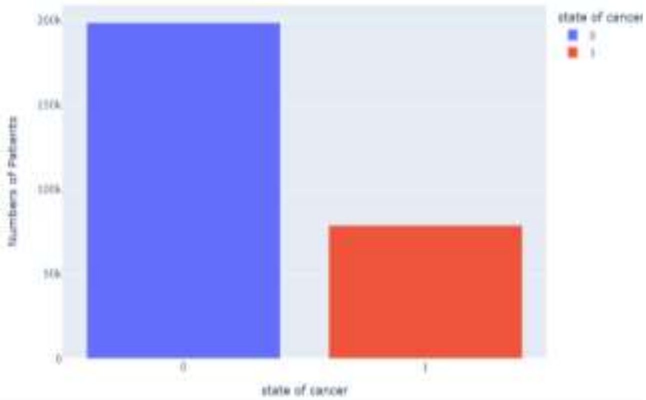

Figure 8. *The data distribution dynamics in the data set*

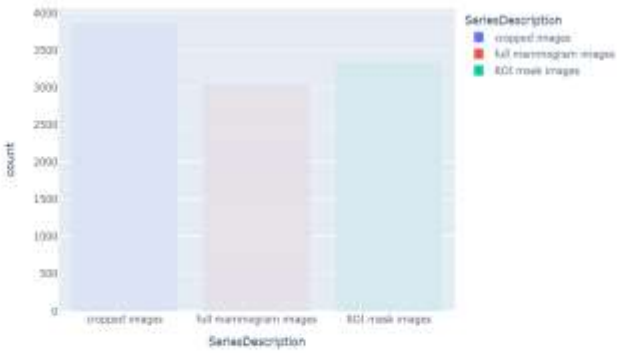

Figure 9. *The dataset distribution dynamics consisting of crop images, full mammogram images, and ROI mask images*

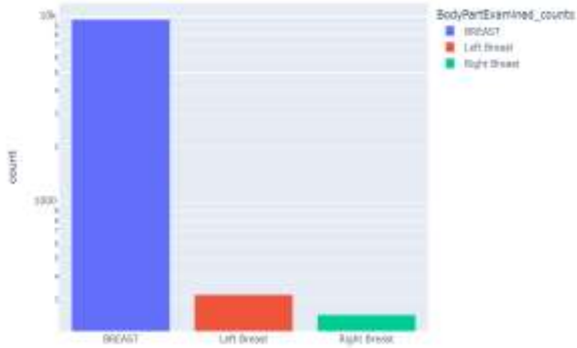

Figure 10. *Mammography data dynamics*

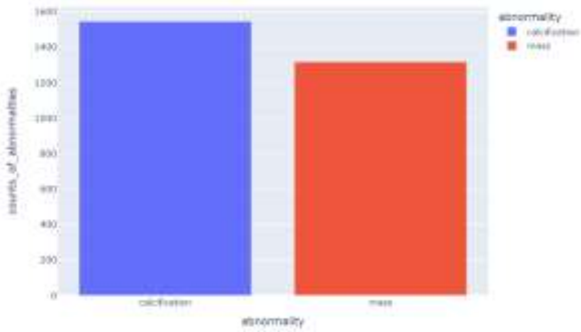

Figure 11. *Data distribution dynamics in terms of calcification of abnormality and mass abnormality*

calcification abnormality are visualized. As president Figure 13, an excerpt from different types of calcification samples is provided, reflecting both affected and healthy samples. As presented in Figure 14, it is observed that the ground truth values are contrasted with the predictions of the suggested model in order to assess the model's performance. As presented in Figure 15, the results of breast cancer probability are provided for the given test sample. It shows a breast cancer probability of 1.0, reflecting the highest probability of breast cancer. The accuracy of the suggested model is plotted versus the number of epochs in terms of both training and test accuracy, as shown in Figure 16. The findings indicate that the accuracy of the model is influenced by the number of epochs.

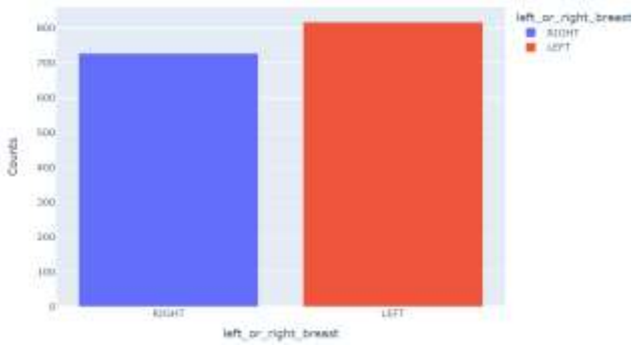

Figure 12. *Data distribution in terms of left or right breast linked to calcification abnormality*

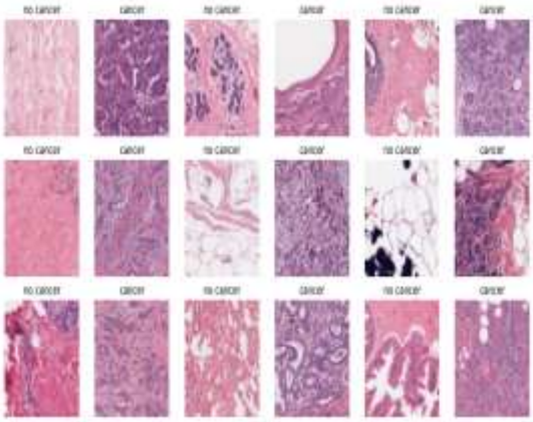

Figure 13. *Cancer and healthy samples associated with different types of calcification*

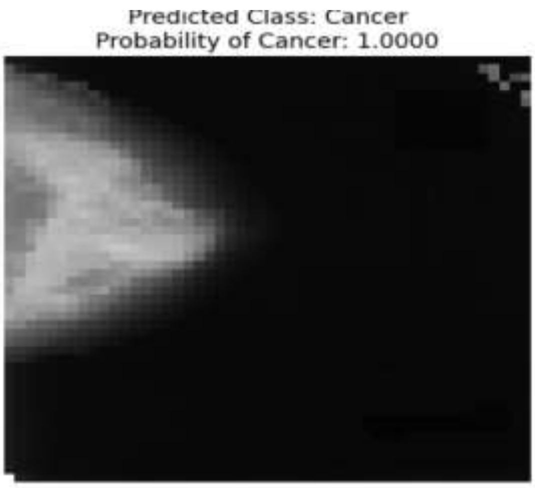

Figure 14. *The results of the probability of breast cancer*

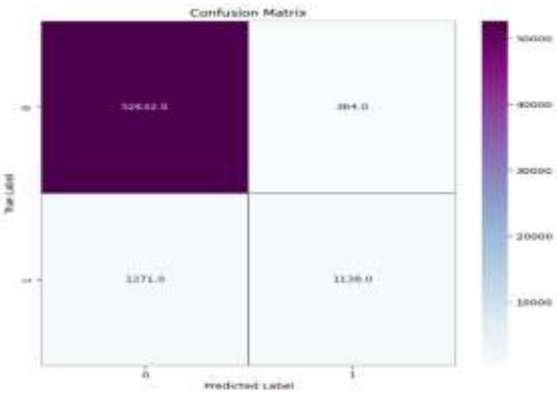

Figure 15. *Results of experiments in terms of confusion matrix*

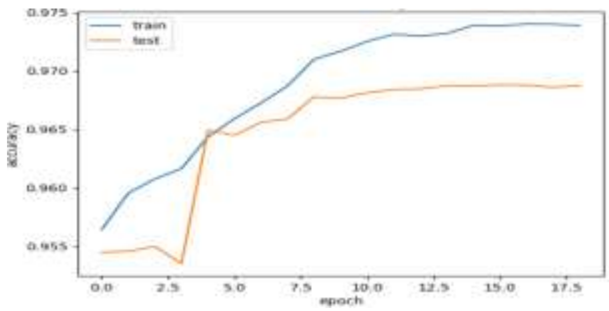

Figure 16. *Results of experiments on the accuracy of training and testing*

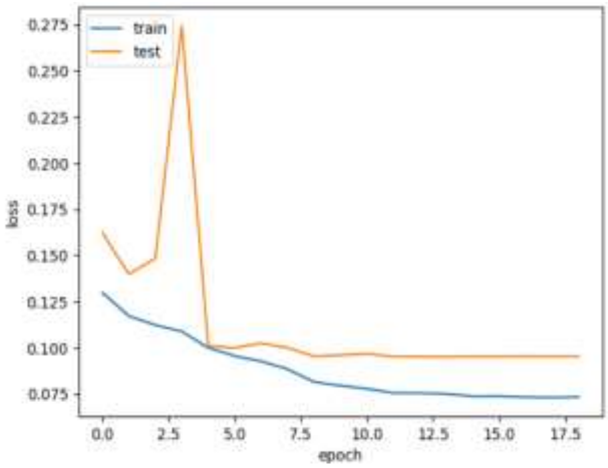

Figure 17. *Results of experiments on training and testing loss*

In other words, the model accuracy progressively rises until convergence as the number of epochs grows. Figure 17 illustrates the loss of the proposed model in terms of both training and test loss as a function of epochs. Results show that the model's loss depends on the number of epochs. Put another way, the model loss progressively drops until convergence as the number of epochs rises.

5. Discussion

Breast cancer research with the help of artificial intelligence is a significant area due to its learning-based approach, which could increment knowledge from time to time.

Artificial intelligence-enabled approaches for medical image analysis are becoming very popular. AI-enabled approaches are widely used to solve problems in the healthcare domain. With respect to breast cancer screening, there are many imaging modalities available. In this research, we used breast mammograms as an imaging modality.

The rationale behind this is that mammogram images are found to be more suitable for breast cancer screening. We proposed a deep learning framework that has mechanisms to exploit training samples and perform automatic breast cancer detection. The supervised learning approach that the framework is built on is intended to automatically detect breast cancer.

Based on the CNN model, a deep learning model is suggested for effectively identifying breast cancer in the breast mammography pictures. The suggested deep learning model was tested using evaluated and found to detect breast cancer more accurately. Our empirical evolution revealed that a large number of cutting-edge deep learning models are outperformed by the suggested model; however, the proposed methodology has certain limitations, as discussed in Section 5.1.

5.1 Limitations

The proposed research presented in this paper has certain limitations. The breast mammogram images available in the dataset are limited in number. Without sufficient diversity of training samples, it is difficult to generalize the findings of breast cancer detection. Another important limitation found in this research is that the proposed framework relies on enhanced CNN model without considering other options like hybridization of deep learning models and creating a collection of several deep learning models towards leveraging performance and detection process.

6. Conclusion and future work

This research presents an improved CNN model known as Breast Cancer Detection Network (BCDNet), specifically designed for improved efficiency in analyzing breast mammogram images. BCDNet model can perform feature extraction, feature optimization, and breast cancer detection. It is based on the supervised learning process in which experts train samples to gain knowledge and use the same for automatic breast cancer detection. In the empirical study, mammogram images are used as they are better than many other imaging modalities. Additionally, we introduce an algorithm, Learning-Based Cancer Screening (LBCS), which utilizes the BCDNet model. An empirical study using the CBID-DDSM benchmark dataset demonstrated that BCDNet outperforms many existing deep learning models and achieves the highest accuracy of 97.68%. As part of a CDSS, healthcare facilities can utilize this model to test for breast cancer. We plan to enhance our breast cancer detection methodology in our future work by utilizing hybrid deep-learning models. Another area for future work involves creating an ensemble deep-learning model to improve detection performance further. Convolutional neural networks is an important tool and used in many different application [41-54].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Leila Abdelrahman; Manal Al Ghamdi; Fernando Collado-Mesa and Mohamed Abdel-Mottaleb;. (2021). Convolutional neural networks for breast cancer detection in mammography: A survey. *Computers in Biology and Medicine*. 131:104248 http://doi:10.1016/j.compbiomed.2021.104248

[2] Elaheh Tarighati Sereshkeh, Hadi Keivan, Kiarash Shirbandi, Fatemeh Khaleghi and Mohammad Mahdi Bagheri Asl. (2024). A convolution neural network for rapid and accurate staging of breast cancer based on mammography. *Informatics in Medicine unlocked* 47;101497. https://doi.org/10.1016/j.imu.2024.101497

[3] Md Rakibul Islam, Md Mahbubur Rahman, Md Shahin Ali, Abdullah Al Nomaan Nafi, Md Shahariar Alam, Tapan Kumar Godder, Md Sipon Miah and Md Khairul Islam. (2024). Enhancing breast cancer segmentation and classification: An Ensemble Deep Convolutional Neural Network and U-net approach on ultrasound images. *Machine Learning with Applications* 16,100555. https://doi.org/10.1016/j.mlwa.2024.100555

[4] Laxman Singh and Altaf Alam. (2022). An efficient hybrid methodology for an early detection of breast cancer in digital mammograms. *Springer*. *J Ambient Intell Human Comput* 15, 337–360 https://doi.org/10.1007/s12652-022-03895-w

[5] Rengarajan Karthiga, Kumaravelu Narasimhan, Ravikumar Chinthaginjala, Rajesh Anbazhagan, Manikandan Chinnusamy, Giovanni Pau, Kumar Satish, Rengarajan Amirtharajan, and Mohamed Abbas. (2024). A novel exploratory hybrid deep neural network to predict breast cancer for mammography based on wavelet features. *Multimed Tools Appl* 83, 65441–65467. https://doi.org/10.1007/s11042-023-18012-y

[6] SOUMYA SARA KOSHY AND L. JANI ANBARASI. (2024). LMHistNet: Levenberg–Marquardt Based Deep Neural Network for Classification of Breast Cancer Histopathological Images. *IEEE Transactions on Transportation Electrification*. 12, pp.52051 - 52066. DOI:10.1109/ACCESS.2024.3385011

[7] MUHAMMAD ANAS, IHTISHAM UL HAQ, GHASSAN HUSNAIN, AND SYED ALI FARAZ JAFFERY. (2024). Advancing Breast Cancer Detection: Enhancing YOLOv5 Network for Accurate Classification in Mammogram Images. *IEEE Access,* 12;16474-16488. DOI:10.1109/ACCESS.2024.3358686

[8] Xin Wen, Xing Guo, Shuihua Wang, Zhihai Lu and Yudong Zhang. (2024). Breast cancer diagnosis: A systematic review. *Biocybernetics and Biomedical Engineering*. 44(1),119-148. https://doi.org/10.1016/j.bbe.2024.01.002

[9] DILAWAR SHAH, MOHAMMAD ASMAT ULLAH KHAN, MOHAMMAD ABRAR, FARHAN AMIN, BADER FAHAD ALKHAMEES, AND HUSSAIN ALSALMAN. (2024). Enhancing the Quality and Authenticity of Synthetic Mammogram Images for Improved Breast Cancer Detection. *IEEE Access,* 12;90535-9055112. DOI:10.1109/ACCESS.2024.3354826

[10] Ling Tan, Ying Liang, Jingming Xia*, Hui Wu, and Jining Zhu. (2024). Detection and Diagnosis of Small Target Breast Masses Based on Convolutional Neural Networks. *IEEE*. 29(5), pp.1524 - 1539. http://DOI:10.26599/TST.2023.9010126

[11] Mahnoosh Torabi, Amir Hosein Rasouli, Q.M. Jonathan Wu, Weipeng Cao and Farhad Pourpanah. (2024). Self-supervised adversarial adaptation network for breast cancer detection. *Engineering Applications of Artificial Intelligence* 133;108489 https://doi.org/10.1016/j.engappai.2024.108489

[12] ZAHARADDEEN SANI, RAJESH PRASAD, AND EZZEDDIN KAMIL MOHAMED HASHIM. (2023). Breast Cancer Classification Using Equivariance Transition in Group Convolutional Neural Networks. *IEEE Access,* 12;118938-118938. DOI:10.1109/ACCESS.2023.3253640

[13] Kosmia Loizidou, Rafaella Elia and Costas Pitris. (2023). Computer-aided breast cancer detection and classification in mammography: A comprehensive review. *Computers in Biology and Medicine* 153;106554. https://doi.org/10.1016/j.compbiomed.2023.106554

[14] Bita Asadi and Qurban Memon. (2023). Efficient breast cancer detection via cascade deep learning network. *International Journal of Intelligent Networks*4;46-52. https://doi.org/10.1016/j.ijin.2023.02.001

[15] Kushangi Atrey Bikesh Kumar Singh, Narendra K. Bodhey and Ram Bilas Pachori. (2023). Mammography and ultrasound based dual modality classification of breast cancer using a hybrid deep learning approach. *Biomedical Signal Processing and Control* 86(A), pp.1-27. https://doi.org/10.1016/j.bspc.2023.104919

[16] Gami, B., Chauhan, K., Panchal, B.Y. (2023). Breast Cancer Detection Using Deep Learning. In: Marriwala, N., Tripathi, C., Jain, S., Kumar, D. (eds) Mobile Radio Communications and 5G Networks. Lecture Notes in Networks and Systems, 588. Springer, Singapore. https://doi.org/10.1007/978-981-19-7982-8_8

[17]Steven J. Frank. (2023). A deep learning architecture with an object-detection algorithm and a convolutional neural network for breast mass detection and visualization. *Healthcare Analytics* 3;1001863. https://doi.org/10.1016/j.health.2023.100186

[18] K. B. Saran, G. Sreelekha and V. C. Sunitha, "Breast Density Classification to Aid Clinical Workflow in Breast Cancer Detection Using Deep Learning Network," TENCON 2023 - 2023 IEEE Region 10 Conference (TENCON), Chiang Mai, Thailand, 2023, pp. 444-449, doi: 10.1109/TENCON58879.2023.10322346.

[19]Subasish Mohapatra, Sarmistha Muduly, Subhadarshini Mohanty, J V R Ravindra and Sachi Nandan Mohanty. (2022). Evaluation of deep learning models for detecting breast cancer using histopathological mammograms Images. *Sustainable Operations and Computers* 3,296-302. https://doi.org/10.1016/j.susoc.2022.06.001

[20] Hana Mechria, Khaled Hassine and Mohamed Salah Gouider. (2022). Breast cancer detection in mammograms using deep learning. 207,2345-2352. *Procedia Computer Science* https://doi.org/10.1016/j.procs.2022.09.293

[21] Daniel g. p. petrini, carlos shimizu, rosimeire a. roela, gabriel vansuita valente, maria aparecida azevedo koike folgueira and hae yong kim. (2022). Breast Cancer Diagnosis in Two-View Mammography Using End-to-End Trained EfficientNet-Based Convolutional Network. *IEEE*. 10, pp.77723 - 77731. DOI:10.1109/ACCESS.2022.3193250

[22] Hanan Aljuaid, Nazik Alturki, Najah Alsubaie, Lucia Cavallaro and Antonio Liotta. (2022). Computer-aided diagnosis for breast cancer classification using deep neural networks and transfer learning. *Computer Methods and Programs in Biomedicine* 223;106951. https://doi.org/10.1016/j.cmpb.2022.106951

[23] Omonigho, Emmanuel Lawrence; David, Micheal; Adejo, Achonu and Aliyu, Saliyu (2020). International Conference in Mathematics, Computer Engineering and Computer Science (ICMCECS) - *Breast Cancer:Tumor Detection in Mammogram Images Using Modified AlexNet Deep Convolution Neural Network.* 1–6. http://doi:10.1109/ICMCECS47690.2020.240870

[24] Agnes, S. Akila; Anitha, J.; Pandian, S. Immanuel Alex and Peter, J. Dinesh (2020). Classification of Mammogram Images Using Multiscale all Convolutional Neural Network (MA-CNN). *Journal of Medical Systems,* 44(1), 30–. http://doi:10.1007/s10916-019-1494-z

[25] Sobia Shakeel and Gulistan Raja; (2021). Classification of Breast Cancer from Mammogram images using Deep Convolution Neural Networks . *2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST).* http://doi:10.1109/ibcast51254.2021.9393191

[26] Yurttakal, Ahmet Haşim; Erbay, Hasan; İkizceli, Türkan and Karaçavuş, Seyhan (2019). Detection of breast cancer via deep convolution neural networks using MRI images. *Multimedia Tools and Applications.* http://doi:10.1007/s11042-019-7479-6

[27] Naveed Chouhan; Asifullah Khan; Jehan Zeb Shah; Mazhar Hussnain and Muhammad Waleed Khan; (2021). Deep convolutional neural network and emotional learning based breast cancer detection using digital mammography. *Computers in Biology and Medicine.* http://doi:10.1016/j.compbiomed.2021.104318

[28] Ekici, Sami and Jawzal, Hushang (2020). Breast cancer diagnosis using thermography and convolutional neural networks. *Medical Hypotheses,* 137, 109542–. http://doi:10.1016/j.mehy.2019.109542

[29] Hassan, Shaymaâ□□a A.; Sayed, Mohammed S.; Abdalla, Mahmoud I and Rashwan, Mohsen A. (2020). Breast cancer masses classification using deep convolutional neural networks and transfer learning. *Multimedia Tools and Applications.* http://doi:10.1007/s11042-020-09518-w

[30] Renuka Nagpure; Sumita Chandak and Nileema Pathak; (2020). Breast Cancer Detection using Neural Network Mammogram . *2020 International Conference on Convergence to Digital World - Quo Vadis (ICCDW).* http://doi:10.1109/iccdw45521.2020.9318635

[31] Djebbar, Kadda; Mimi, Malika; Berradja, Khadidja and Taleb-Ahmed, Abdelmalik (2019). 6th International Conference on Image and Signal Processing and their Applications (ISPA) - Deep convolutional neural networks for detection and classification of tumors in mammograms. 1–7. http://doi:10.1109/ISPA48434.2019.8966895

[32] T. Kavitha; Paul P. Mathai; C. Karthikeyan; M. Ashok; Rachna Kohar; J. Avanija and S. Neelakandan; (2021). Deep Learning Based Capsule Neural Network Model for Breast Cancer Diagnosis Using Mammogram Images. *Interdisciplinary Sciences: Computational Life Sciences.* http://doi:10.1007/s12539-021-00467-y

[33] Patil, Rajeshwari S. and Biradar, Nagashettappa (2020). Automated mammogram breast cancer detection using the optimized combination of convolutional and recurrent neural network. *Evolutionary Intelligence.* http://doi:10.1007/s12065-020-00403-x

[34] Shu, Xin; Zhang, Lei; Wang, Zizhou; Lv, Qing and Yi, Zhang (2020). Deep Neural Networks with Region-based Pooling Structures for Mammographic Image Classification. *IEEE Transactions on Medical Imaging,* 1–1. http://doi:10.1109/TMI.2020.2968397

[35] Wessam M. Salama and Moustafa H. Aly; (2021). Deep learning in mammography images segmentation and classification: Automated CNN approach. *Alexandria Engineering Journal.* http://doi:10.1016/j.aej.2021.03.048

[36] Sun, Lilei; Wang, Junqian; Hu, Zhijun; Xu, Yong and Cui, Zhongwei (2019). Multi-view convolutional neural networks for mammographic image classification. *IEEE Access,* 1–1. http://doi:10.1109/ACCESS.2019.2939167

[37] Andrés anaya-isaza, leonel mera-jiménez, johan manuel cabrera-chavarro, lorena guachi-guachi, diego peluffo-ordóñez, and jorge ivan rios-patiño. (2021). Comparison of Current Deep Convolutional Neural Networks for the Segmentation of Breast Masses in Mammograms. *IEEE*. 9, pp.152206 - 152225. DOI:10.1109/ACCESS.2021.3127862

[38] Chatsuda Songsaeng; Piyanoot Woodtichartpreecha and Sitthichok Chaichulee; (2021). Multi-Scale Convolutional Neural Networks for Classification of Digital Mammograms With Breast Calcifications. *IEEE Access.* http://doi:10.1109/access.2021.3104627

[39] Khan, Hasan Nasir; Shahid, Ahmad Raza; Raza, Basit; Dar, Amir Hanif and Alquhayz, Hani (2019). Multi-View Feature Fusion-based Four Views Model for Mammogram Classification using Convolutional Neural Network. *IEEE Access,* 1–1. http://doi:10.1109/ACCESS.2019.2953318

[40] Meenalochini, G. and Ramkumar, S. (2020). Survey of machine learning algorithms for breast cancer detection using mammogram images. *Materials Today: Proceedings,* S2214785320364257–. http://doi:10.1016/j.matpr.2020.08.543

[41]Priti Parag Gaikwad, & Mithra Venkatesan. (2024). KWHO-CNN: A Hybrid Metaheuristic Algorithm Based Optimzed Attention-Driven CNN for Automatic Clinical Depression Recognition . *International Journal of Computational and Experimental Science and Engineering,* 10(3). https://doi.org/10.22399/ijcesen.359

[42]KIRELLİ, Y., & AYDIN, G. (2023). Classification of Histopathological Images in Automatic Detection of Breast Cancer with Deep Learning Approach. *International Journal of Computational and Experimental Science and Engineering*, 9(4), 359–367. Retrieved from https://www.ijcesen.com/index.php/ijcesen/article/view/279

[43]Agnihotri, A., & Kohli, N. (2024). A novel lightweight deep learning model based on SqueezeNet architecture for viral lung disease classification in X-ray and CT images. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.425

[44]Radhi, M., & Tahseen, I. (2024). An Enhancement for Wireless Body Area Network Using Adaptive Algorithms. *International Journal of Computational and Experimental Science and Engineering,* 10(3). https://doi.org/10.22399/ijcesen.409

[45]LAVUDIYA, N. S., & C.V.P.R Prasad. (2024). Enhancing Ophthalmological Diagnoses: An Adaptive Ensemble Learning Approach Using Fundus and OCT Imaging. *International Journal of Computational and Experimental Science and*

Engineering, 10(4). https://doi.org/10.22399/ijcesen.678

[46]Sashi Kanth Betha. (2024). ResDenseNet:Hybrid Convolutional Neural Network Model for Advanced Classification of Diabetic Retinopathy(DR) in Retinal Image Analysis. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.693

[47]Boddupally JANAIAH, & Suresh PABBOJU. (2024). HARGAN: Generative Adversarial Network BasedDeep Learning Framework for Efficient Recognition of Human Actions from Surveillance Videos. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.587

[48]KUKUK, S. B., & KİLİMCİ, Z. H. (2021). Comprehensive Analysis of Forest Fire Detection using Deep Learning Models and Conventional Machine Learning Algorithms. *International Journal of Computational and Experimental Science and Engineering*, 7(2), 84–94. Retrieved from https://www.ijcesen.com/index.php/ijcesen/article/view/152

[49]L. Smitha, Maddala Vijayalakshmi, Sunitha Tappari, N. Srinivas, G. Kalpana, & Shaik Abdul Nabi. (2024). Plant Disease Detection Using CNN with The Optimization Called Beluga Whale Optimization Mechanism. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.697

[50]J Jeysudha, K. Deiwakumari, C.A. Arun, R. Pushpavalli, Ponmurugan Panneer Selvam, & S.D. Govardhan. (2024). Hybrid Computational Intelligence Models for Robust Pattern Recognition and Data Analysis . *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.624

[51]T. Deepa, & Ch. D. V Subba Rao. (2025). Brain Glial Cell Tumor Classification through Ensemble Deep Learning with APCGAN Augmentation. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.803

[52]S. Amuthan, & N.C. Senthil Kumar. (2025). Emerging Trends in Deep Learning for Early Alzheimer's Disease Diagnosis and Classification: A Comprehensive Review. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.739

[53]URAL, A., & KİLİMCİ, Z. H. (2021). The Prediction of Chiral Metamaterial Resonance using Convolutional Neural Networks and Conventional Machine Learning Algorithms. *International Journal of Computational and Experimental Science and Engineering*, 7(3), 156–163. Retrieved from https://www.ijcesen.com/index.php/ijcesen/article/view/165

[54]PATHAPATI, S., N. J. NALINI, & Mahesh GADIRAJU. (2024). Comparative Evaluation of EEG signals for Mild Cognitive Impairment using Scalograms and Spectrograms with Deep Learning Models. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.534