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RESEARCH ARTICLE

Breast Cancer Detection Using Deep Learning: An Investigation Using the DDSM Dataset and a Customized AlexNet and Support Vector Machine

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ABSTRACT The most lethal and devastating form of cancer, breast cancer, is often first detected when a lump appears in the breast. The cause can be attributed to a typical proliferation of cells in the mammary glands. Early breast cancer detection improves survival. Breast cancer screening and early detection are commonly carried out using imaging techniques such as mammography and ultrasound. Convolutional neural networks (CNNs) can identify breast cancer on mammograms. Layers of artificial neurons detect patterns and properties in images to help identify abnormalities more accurately. CNNs may be trained on large datasets to improve accuracy and handle more complex visual information than traditional methods. We introduced a unique approach termed BreastNet-SVM with the objective of automating the identification and categorization of breast cancer in mammograms. This study uses a nine-layer model with two fully connected layers to retrieve data features. Furthermore, we utilized support vector machines (SVM) for classification purposes. To conduct this experiment, we used a well-known benchmark dataset Digital Database for Screening Mammography (DDSM). It is shown that the suggested model has a 99.16% accuracy rate, a 97.13% sensitivity rate, and a 99.30% specificity rate. The top approaches for detecting breast cancer were compared to the recommended BreastNet-SVM model. In terms of accuracy, the proposed BreastNet-SVM model fared better in experimental results on a DDSM dataset.

INDEX TERMS Breast cancer, mammography, digital database for screening mammography, AlexNet, support vector machine.

I. INTRODUCTION

Women in developed nations die most from breast cancer [1]. Early detection is the most powerful weapon in the fight against breast cancer. A precise and trustworthy diagnostic method is needed to help doctors tell benign from malignant breast cancers before undergoing invasive surgery. The goal of these forecasts is to classify patients into two groups: those with benign conditions and those with malignant ones.

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Only a biopsy can definitively determine if there is cancer in the breast; doctors, self-examination, and imaging tools cannot. The use of imaging technologies, such as mammography, ultrasound, and magnetic resonance imaging, is now the main strategy used for the early identification of breast cancer. Nevertheless, restrictions, including the need for X-rays, costs, the presence of thick tissue in young patients, and the frequency of incorrect positive and negative results, have forced researchers and organizations to investigate other strategies [2].

Breast cancer detection through mammography screening is a commonly utilized technique.

The breast is imaged using X-rays in this procedure. Women who are asymptomatic have screening mammograms to look for early, clinically undetected breast cancer. Breast cancer treatment choices and survival rates are improved when the disease is discovered early by screening and diagnostic mammography. However, a considerable degree of inaccuracy may be introduced into the identification of suspected anomalies because of the human element engaged in the screening process.

According to research, radiologists make mistakes in the diagnosis of cancer during screening studies at a rate of 10% to 30%. 52% of mistakes are the result of incorrect interpretation of breast cancer symptoms, and 43% of errors are the result of failing to notice symptoms in abnormal scans [3].

This error rate leads to numerous biopsies being done on benign lesions, which causes unnecessary expense and distress for the patient. Errors brought on by incorrect mammography categorization have a high financial impact. This is due to the fact that false negatives in screening mammography are a major issue since early identification may significantly lower treatment costs, times, and efficacy. False negatives have an impact on all three factors since an inaccurate diagnosis prevents early detection.

When screening mammography is read twice instead of once, the sensitivity is higher without affecting recall rates. However, a significant disadvantage of this strategy is personnel. For the double reading of mammograms, a significant number of radiologists will be needed. As a consequence, many countries may not be able to provide enough people for such a strategy.

Radiologists' reliance on visual examination is a primary factor in these mistakes. Radiologists may get quickly fatigued when manually screening a large number of mammograms, overlooking important cues while analyzing the images. Massive efforts are being undertaken to automate the mammographic screening process in order to counteract these impacts.

Due to its superior performance in a number of machine learning tasks, including object classification and detection, deep learning (DL) is now widely considered a cutting-edge methodology [4].

The concept of machine learning involves using data samples to solve learning problems and make inferences, and it is a key component of artificial intelligence. Machines can learn from data without requiring explicit programming. It employs 120 unique mathematical, statistical, and logical techniques to accomplish this [5]. Machine learning (ML) methods are commonly used to classify images. ML algorithms must extract characteristics from the images in order to identify things. The Support Vector Machine (SVM), a supervised learning technology used for data categorization, is one such approach.

By creating hyperplanes in a high-dimensional feature space, the SVM algorithm aims to efficiently separate data points. Multiple hyper-planes exist for dividing up a pair of datasets. The hyper-plane with the largest margin is the best option. The margin is the maximum distance that the boundary could expand before it would enclose a given data point [6]. The points that establish the margin are known as the support vectors. The optimum hyperplane that divides the target vector clusters in the two dimensions is what the SVM aims to find.

Deep learning is a well-known ML technique that has excelled in many different fields. These fields include robotics, NLP, agriculture, medicine, and more. Jayandhi et al. [7] introduced a powerful Support Vector Machine (SVM)-based Deep Learning Architecture (DLA) for diagnosing breast cancer. Utilizing the advanced Visual Geometric Group (VGG) design, the study employs 16 layers and compact 3×3 convolution filters to reduce the intricacy of the system.

CNN is a well-known and effective deep-learning method. Used often in data science applications, such as the classification of medical images and the extraction of features from training photos, are trained convolutional neural network (CNN) models [8]. To put it another way, CNN is designed to find and extract high-level features that can distinguish between different class labels in a classification task.

Tan et al. [9] suggested a method in which, before sending the mammograms to the computer, they are preprocessed to produce an image that can be recognized automatically. The CNN model will use a variety of features derived from the image to distinguish between each set of labeled data. Following 20,000 comparisons, a model that can classify input images into the most accurate results will be produced. The model has to be trained only once.

There are a plethora of public and private breast cancer datasets available, all of which contribute to the advancement of early detection methods. Maqsood et al. [10] put forward a system for "end-to-end" training that may identify breast cancer during mammography screening. A texture convolutional neural network (TTCNN) that uses an energy layer to extract texture features improves the detail in images, and the improved accuracy of the extracted features improves the network's classification abilities. The method achieved a mean accuracy of 97.49% across three separate tests on the MIAS, INbreast, and DDSM datasets.

In a separate investigation, Tavakoli et al. [11] developed a method for distinguishing between healthy and sick breast tissues at the cellular level. The method incorporates preprocessing, a novelty-architected block-based CNN, and a decision mechanism. Once CNN is taught to classify pixels in the ROI as abnormal or normal, a binary map is generated. It achieved a 94.68% accuracy rate and a 0.95 AUC on the MIAS database. Future studies should enhance CNN's feature extraction, lessen false positives, and assess the system using different clinical databases.

In order to diagnose breast cancer using cutting-edge ML and DL methods, a number of techniques have been proposed. The effectiveness of early breast cancer detection, however, is still a subject of debate.

Therefore, a comprehensive strategy is suggested for a quick and accurate diagnosis of breast cancer. The principal contributions are as follows:

Model Introduced: For the purpose of detecting breast cancer, the paper proposes a unique model that combines SVM with the Modified AlexNet architecture. By combining their capabilities, deep learning-based feature extraction with the SVM classifier may more accurately and quickly diagnose breast cancer.

AlexNet adaptation: This work investigates how to modify the original AlexNet design to identify breast cancer in mammography images. The Modified AlexNet is tuned and customized to capture pertinent and significant features specific to breast cancer.

Transfer Learning: Using pre-learned weights from a sizable dataset in the Modified AlexNet architecture, the study applies transfer learning. This method enhances feature extraction and expands the model's ability to extract breast cancer-related discriminative features by utilizing previously learned representations.

The valuable DDSM dataset, known as the Digital Database for Screening Mammography, is utilized in the research. The paper presents a thorough evaluation of the suggested model, considering several performance indicators, including accuracy, sensitivity, and specificity. Through these evaluations, the model's capability to classify mammography images and detect breast cancer is confirmed.

Potential Clinical Impact: The study emphasizes the proposed model's potential clinical implications. It may lead to earlier detection, better treatment planning, and possibly better patient outcomes if radiologists use the model to quickly and accurately diagnose breast cancer.

The primary contributions of the study include the creation of an innovative model for detecting breast cancer that integrates the Modified AlexNet architecture and SVM, the customization and refinement of the AlexNet architecture for analyzing mammograms, the utilization of the DDSM dataset for both training and assessment purposes, and the assessment of the model's efficacy through diverse metrics. The aforementioned contributions improve the efficacy of computer-aided breast cancer detection and offer novel avenues for further research to enhance breast cancer diagnosis.

II. RELATED WORK

The following section examines recent studies on deep learning techniques and their application in identifying and categorizing breast cancer.

Moon et al. [12] use a technique of image fusion together with several image content representations, as well as a collection of various CNN architectures, to suggest a CAD system for tumor identification. The ensemble method's diagnostic performance was 91.10%, 85.14%, 95.77%, and 0.9697, respectively. Skip connection was utilized by ResNet and DenseNet to correct messages, prevent inter-layer transmission loss, and address gradient disappearance. Experts manually clip the region of interest (ROI) and tumor contour in the B-mode ultrasound (US) image. However, different operators may generate varying ROI regions and tumor contours. This presents one of the current limitations of the study.

In their study, Khan et al. [13] presented a deep learning approach that employs transfer learning for the identification and classification of breast cancer. To increase classification accuracy, GoogleNet, VGGNet, and ResNet—three distinct CNN architectures—were integrated. Data augmentation made CNN more effective. 97.525% more accurate than competing techniques. In subsequent developments, a fusion of manually designed features and CNN features will be employed to enhance the classification process.

Saber et al. [14] put forward a deep learning framework to improve the classification results of the MIAS dataset, aiming at the detection and diagnosis of breast cancer. The dataset underwent preprocessing steps, including noise reduction, contrast enhancement, and identification of malignant regions. Added data augmentation to expand the dataset. they improved mass-lesion classification through the use of fine-tuning and freezing techniques. When compared to the other models, VGG16 performed the best. The study has an AUC of 0.995 and an accuracy of 98.96%.

Sivanandan and Jayakumari [15] utilized the StepNet convolutional neural network (CNN) structure to extract and categorize characteristics of breast tumors from ultrasound images. StepNet employs a progressive convolution approach, allocating fewer convolutions for low-level features and more for high-level features. The network employs leaky ReLU activation and takes both original and preprocessed images as input. The validation process involves clustering the final activation maps. By means of preprocessing and augmentation techniques, StepNet achieved a validation accuracy of 0.988. Nonetheless, it was unable to detect highly intense isoechoic lesions.

Wang et al. [16] suggested using a modified version of the EfficientNet CNN architecture to spot cancerous cells in breast tissue. To combat the issue of low image resolution, RCC data augmentation was used to maintain resolution while protecting crucial parts of the image. For training on low-resolution pictures, RDS lowered the down-sampling scale. Performance was enhanced via semantic information enrichment algorithms. Boosted EfficientNet-B3 outperformed ResNet50 and DenseNet121 in terms of performance. The method has the potential to enhance illness diagnosis in various models. achieved 97.96% accuracy and 99.68% AUC, providing medical institutions with a quick and dependable replacement.

In order to mitigate training bias and overfitting, Zuluaga-Gomez et al. [2] put forward a convolutional neural network (CNN) strategy for thermal image-based breast cancer diagnosis. The DMR-IR study demonstrated that splitting the database helps mitigate overfitting and bias. The research examined several CNN architectures on DMR-IR and optimized their hyperparameters. The best CNN model has a 92% F1 score, 94% accuracy, 94% precision, and 91% sensitivity. New public datasets posing multi-class categorization difficulties need further study and funding.

Alruwaili et al. [2] that focus on using deep learning models for improving diagnostic mammography methods for detecting breast cancer. The researchers employed transfer learning with pre-trained models, specifically ResNet50

TABLE 1. Overview of current literature review.

Author	Method	Dataset	Year	Limitations	Accuracy (%)
Khan et al. [13]	GoogLeNet, VGGNet, and ResNet	LRH hospital Peshawar, Pakistan	2019	Needs Combined hand-crafted and CNN features for better classification accuracy.	97.52
Elbashir et al. [20]	RNA-Seq-based compact CNN	Pan-Cancer Atlas gene expression data	2019	small dataset limitation	98.76
Moon et al. [12]	Ensemble (WA)	BUSI	2020	Manual cropping of ROIs and tumor contours causes operator variability.	91.10
Zuluaga-Gomez et al. [2]	ResNet, SeResNet, VGG16, Inception, InceptionResNetV2, and Xception	DMR-IR	2020	Lack of thermal image data limits CNN-CAD system generalization	94.0
Toğaçar et al. [18]	convolutional neural network (CNN) that includes an attention module and hypercolumn technique.	BreakHis	2020	BreakHis dataset lacks sample diversity and may be affected by staining and imaging variations.	95.03
Hadush et al. [19]	Designed CNN architecture with RPN and ROI pooling from faster R-CNN for feature extraction.	St.Gebriel Hospital	2020	Model performance can improve with more annotated MG data.	91.86
Saber et al. [14]	Inception-V2 ResNet, VGG-16, VGG-19, ResNet50, and Inception V3	MIAS	2021	Limited Sample Size	98.96
Sivanandan et al. [15]	StepNet	domain-specific dataset of ultrasound breast tumor images	2021	Small datasets may lead to overfitting	91.67
Wang et al. [16]	Boosted EfficientNet model	Rectified Patch Camelyon (RPCam)	2021	Limited exploration of attention mechanisms and feature fusion due to resource constraints.	96.50
Hekal et al. [17]	AlexNet and ResNet-50	CBIS-DDSM ROI	2021	The proposed method needs more features/CNN models to improve classification accuracy	93.2
Jayandhi et al. [7]	VGG-SVM	MIAS	2022	Limited Sample Size	98.67
Maqsood et al. [10]	Transferable texture convolutional neural network (TTCNN)	DDSM	2022	The proposed method needs more features/CNN models to improve classification accuracy	97.49
Tavakoli et al. [11]	Architected block-based CNN	MIAS	2023	The proposed method needs more features/CNN models to improve classification accuracy	94.68

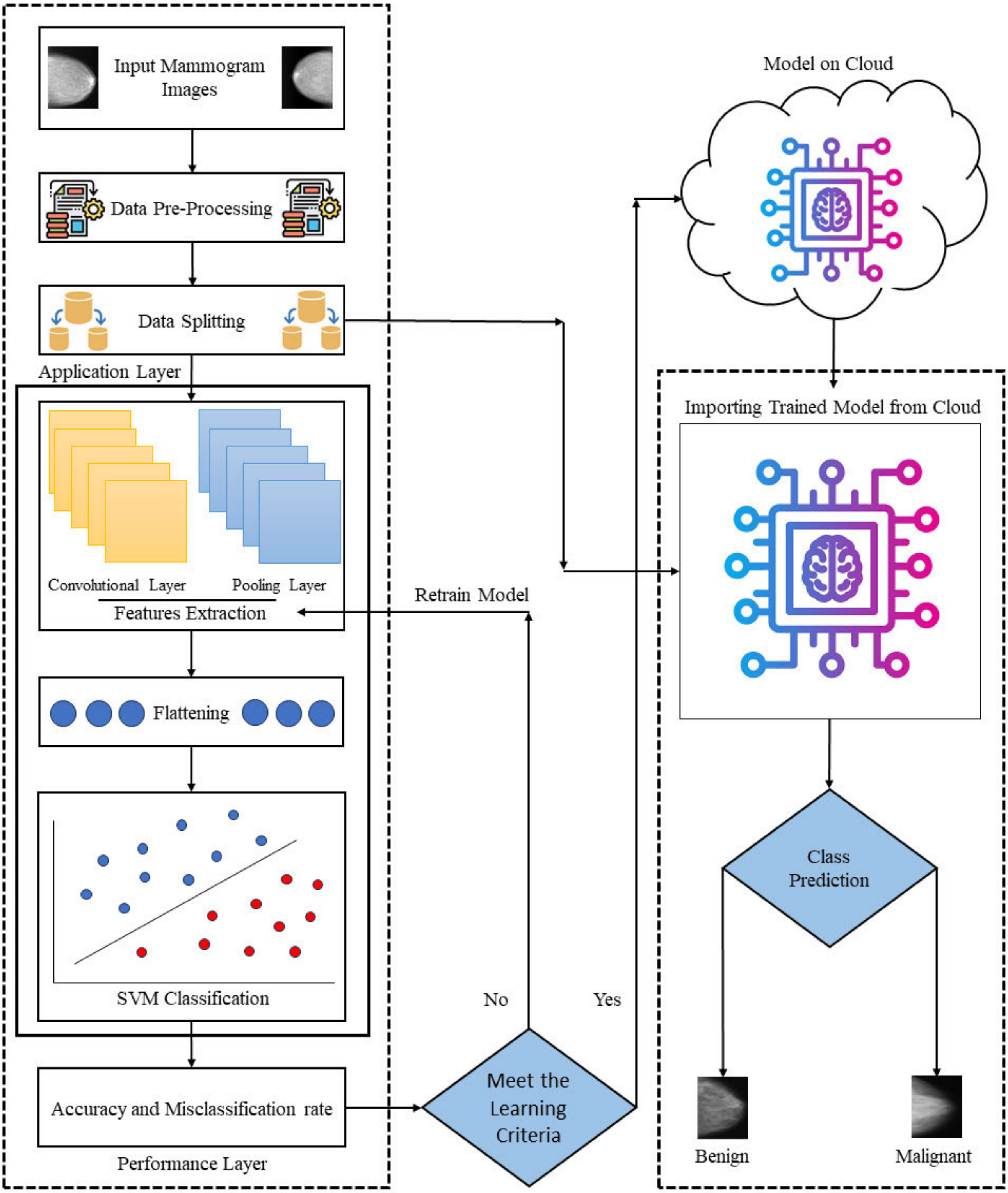

FIGURE 1. The suggested BreastNet-SVM framework.

and Nasnet-Mobile, which were fine-tuned to discriminate between benign and malignant breast cancer cases. They also used augmentation methods to improve the stability of the system, prevent overfitting, and increase the number of mammographic images. The results of their study showed that the suggested deep learning system achieved an accuracy of 89.5 percent using ResNet50 and 70 percent using Nasnet-Mobile on the MIAS dataset. Notably, their DL-based technique outperformed expert radiologists in terms of overall accuracy, precision, recall, and F1-score when using MOD-RES + oversampling (for ResNet50) and Nasnet-Mobile. Comparative experiments demonstrated that their proposed method was more efficient and effective, particularly with limited training datasets, surpassing existing models for medical imaging. This indicates the potential of deep learning techniques in improving the accuracy and efficiency of early detection methods for breast cancer through diagnostic mammography

The deep learning-based CAD method developed by Hekal et al. [17] is intended for early detection of breast cancer. TLR feature extraction utilizes CNN models and variable Otsu thresholding to improve training efficacy. Using a support vector machine (SVM) classifier, mammogram images were sorted into four nodule categories: BC, MC, BM, and MM. Results from experiments with CBIS-DDSM data from ROI demonstrate the method's efficacy. More databases will be tested in the future to determine the system's resilience, and other feature models will be explored to boost speed.

Toğaçar et al. [18] centered on improving the BreakHis data's classification accuracy for the histopathological images that are categorized as benign or malignant. Without preprocessing, the BreastNet model achieved superior or comparable accuracy. At 40X, 100X, 200X, and 400X magnification, the best classification result was 98.51 percent. The classification was improved to 98.80% by adding up all of the magnification factors.

Hadush et al. [19] created a CNN structure that includes the faster R-CNN technique's RPN and ROI pooling. Training and testing on mammogram images yielded an AUC-ROC of 92.2%, 91.86% accuracy for detection, and 94.67% sensitivity. The research suggests increasing the size of the annotated mammography dataset will improve the performance of the models.

Elbashir et al. [20] developed a novel CNN structure for breast cancer classification, utilizing RNA-Seq gene expression data. The Pan-Cancer Atlas provided the data, which was accessed through Illumina's HiSeq platform. To tackle the challenges of small sample size and high dimensionality, a customized CNN architecture with two convolutional layers was devised. Hyperparameters were carefully selected through grid search and five-fold cross-validation. Using CNN to classify cancer into multiple categories will be part of future work.

In this research, we have focused on detecting breast cancer using a repurposed version of the AlexNet architecture. In Table 1, a summary of recent studies that use CNN architectures to detect breast cancer is presented.

According to Table 1, existing CNN-based breast cancer detection techniques are not accurate or efficient in terms of feature extraction. Furthermore, the methods required more time and resources to achieve accuracy. Increased detection accuracy was advocated for in the research project. The data for this study were unevenly distributed, despite the fact that earlier studies used a sophisticated model. As part of this project, we want to create a quick method of diagnosing breast cancer. As a result, we suggest a BreastNet-SVM model that efficiently uses resources while accurately detecting breast cancer.

III. PROPOSED BREASTNET-SVM MODEL

As can be seen in Fig. 1, the proposed BreastNet-SVM model consists of a training and a validation stage. The DDSM dataset, which contains mammograms from women who have been diagnosed with breast cancer, is the first source used. The input images undergo processing in the first step of data preparation to improve the quality of the data prior to the modeling stage. In this step, input images are transformed, noise is removed, and outliers are filtered away. In addition, the input patch may be any of three sizes: 16 by 16, 32 by 32, or 48 by 48. When the data has been cleaned and organized, it is separated into two sets: the training set and the validation set. Eighty percent of the cleaned and prepared data is used for training, with the remaining twenty percent set aside for validation.

The training data is comprised of two distinct components, namely the application layer and the performance layer. Features have been retrieved through the utilization of the BreastNet-SVM modified convolutional neural network at the application layer, as recommended. During the process of feature extraction, significant data is extracted from the input photographs and subsequently transmitted to the subsequent stage. The study employs three optimization algorithms, namely Stochastic Gradient Descent (SGD), Adaptive Moment Estimation (Adam), and Root Mean Square Propagation (RMSprop), in conjunction with hyperparameters set at a learning rate of 0.0001, 50 batches, and 200 epochs. The performance layer was utilized to evaluate the precision and misclassification rate of the BreastNet-SVM model that was suggested. The convolution layer is a fundamental element of a Convolutional Neural Network (CNN) that plays a crucial role in detecting salient features within the input data. The convolutional layers are responsible for executing convolutional operations denoted by the symbol $*$. A filter must be applied to the image before these operations can be performed. An activation map or feature map, two widely used vocabularies, is what emerges from a convolutional operator. Eq. (1) demonstrates the convolutional operation. [21]

$$Z(x, y) = (U * V)(x, y) = \sum_{\mathrm{p}} \sum_{\mathrm{q}} U(p, q)V(x - p, y - q) \tag{1}$$

where V denotes the size of the p x q filter, U denotes the input matrix (image), and Z denotes the feature map's output. The feature map Z is created after the input U and filter V are convolved. By U V, this convolutional operation is represented. Convolutional layer output is forward-directed to a nonlinear activation function (AF). A network gains non-linearity from an activation function. To eliminate linearity and normalize the network values, the activation map can be processed using a variety of nonlinear activation functions, including

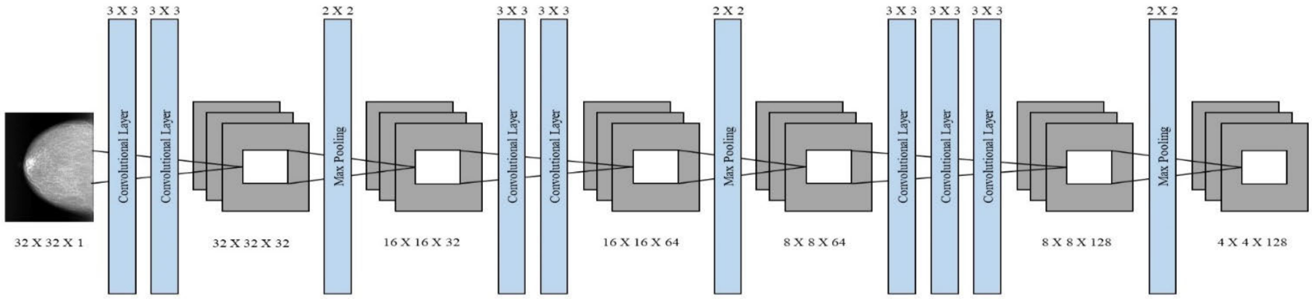

FIGURE 2. **The simplified diagram of the improved AlexNet architecture.**

SoftMax, sigmoid, hyperbolic tangent (Tanh), rectified linear unit (ReLU), and sigmoid. In this study, activation is calculated using the ReLU activation function. The output of the ReLU is zero if the input is zero or less. The numerical values provided in Eq(2) are symbolized by ReLU [22].

$$f(z) = \max(0, z) \tag{2}$$

In the context of a convolutional neural network, the pooling layer is typically employed subsequent to the convolution layer, with the aim of reducing the dimensionality of the feature map while retaining salient features. This phenomenon is commonly referred to as downsampling in academic literature. The pooling layer performs operations such as min pooling, max pooling, sum pooling, and average pooling to lower the activation map's dimension. The pooling layer is meant to reduce the activation map's size while keeping the most relevant data. A flattening operation is performed on the feature map before it is sent to the fully connected layer. Feature map matrix flattening produces a long vector as the result. 80% of the preprocessed mammograms undergo convolutional operations in the convolutional layer. Twelve layers make up the proposed BreastNet-SVM, including three pooling layers, two fully connected layers, and seven convolutional layers. The BreastNet-SVM CNN network architecture is shown in Fig. 2 for the purpose of identifying breast cancer. The proposed network architecture accepts grayscale image input sizes of 16×16, 32×32, and 48×48, as shown in Fig. 2. A total of 32 filters with kernel sizes of 3×3 and the same padding are applied in the first two convolutional layers. The proposed model's non-linearity is eliminated using the ReLU activation function. A max-pooling layer comes after the convolutional layers. We employed two convolutional layers, each with 64 filters, a kernel of 3×3, the same padding, and the ReLU activation function, after downsampling the original $32\times32\times32$ picture using a max-pooling layer using a 2×2 filter and a stride of 2. The next stage is to apply a second max-pooling layer, this time scaling the picture to 8×8 x 64, and using a 2 by 2 kernel size and stride. There are a total of 128 filters used throughout the last three convolutional layers, along with a 33-point kernel and ReLU activation. The third layer of max-pooling uses kernel size, resulting in a size of 4×4 x 128. After that, the third level of max-pooling is applied, which reduces the input space from N dimensions to a single vector of size 2048×1.

The procedures for classifying data using a convolutional neural network are carried out at a Fully Connected (FC) layer after features have been retrieved. The FC layer bridges the gap between the neurons of the preceding layer and those of the layer above. To AF, which generates class scores, is forwarded the output of the fully connected layer. The most popular methods for computing classification purposes are the support vector machine and SoftMax. The SVM classifier is used in the BreastNet-SVM model to achieve the highest level of accuracy in dividing breast cancer into benign and malignant forms. As a result, the performance layer receives these results. Deep learning requires a lot of computational power and training time. To accomplish this, different optimizers significantly contribute to saving computational time and resources. Three optimizers—Adam, RMSprop, and SGD—are used in this study to enhance the performance of the BreastNet-SVM model that is suggested. Adam optimizer uses fewer resources and takes less time to compute, which helps the model learn faster. Adaptive learning rates are utilized by RMSprop, an optimization method used in neural networks. Stochastic gradient descent, a well-known optimization technique in machine learning, leverages model parameters and momentum to discover the optimal fit. Important measures, such as the accuracy and classification rate of the BreastNet-miss SVM, are assessed at the performance layer. There will be a need to retrain the suggested BreastNet-SVM model if the learning criteria do not satisfy the requirements. If the requirements for learning are met, on the other hand, both the findings and the model are saved in the cloud for future use. The validation process begins once the proposed BreastNet-SVM has been trained. At this point, the cloud-stored BreastNet-SVM model is downloaded again so that it may be used to compare the proposed model to the trained one. In this case, the trained BreastNet-SVM model is used to assess 20% of the validation data set. The trained model exhibits a benign classification when cancerous cells are not detected in breast cancer, whereas a malignant classification is displayed when cancer cells are detected.

IV. RESULTS AND DISCUSSION

The DDSM dataset, which is publicly accessible, served as the reference dataset for training and validating the proposed BreastNet-SVM model in this investigation. The BreastNet-SVM model was trained on 80% of the dataset, while the remaining 20% was reserved for model validation. Statistical evaluation metrics like sensitivity, Miss classification rate, Specificity, and Accuracy were used to evaluate the overall performance [23]. The accuracy of the BreastNet-SVM model measures its ability to make accurate predictions, while the miss classification rate indicates the occurrence of erroneous predictions. The subsequent items represent the established criteria.

$$\textit{Accuracy} = \frac{(TN + TP)}{(TN + FP + FN + TP)} \tag{3}$$

$$\textit{Missclassificatiorate} = \frac{(FN + FP)}{(TN + FP + FN + TP)} \tag{4}$$

$$\textit{Sensitivity} = \frac{TP}{(TP + FN)} \tag{5}$$

$$\textit{Specificity} = \frac{TN}{(TN + FP)} \tag{6}$$

The present study proposes the utilization of the BreastNet-SVM model as a means of detecting breast cancer. The recommended methodology, implemented using the Keras tool in Python, employs three optimizers (RMSprop, Adam, and SGD) to produce meaningful results on the DDSM dataset. A comparative analysis is then conducted to evaluate the effectiveness of the proposed BreastNet-SVM model in detecting breast cancer, comparing it to other state-of-the-art methods. Table 2 provides a comparative analysis of the proposed BreastNet-SVM model during the training phase, considering three different input image sizes (16 × 16, 32 × 32, and 48 × 48) and utilizing the Adam, RMSprop, and SGD optimizers.

The proposed BreastNet-SVM model with RMSprop yielded an accuracy of 93.26%, a miss classification rate of 6.74%, a specificity of 97.43%, and a sensitivity of 90.04% with an input image size of 16 × 16. Adam's model has 95.02% accuracy, 4.98% miss classification, 93.34% sensitivity, and 96.66% specificity. The SGD optimizer attained a peak accuracy of 98.85% during the training phase. The model has a 1.15% miss classification rate, 97.93% sensitivity, and 98.94% specificity.

Utilizing the RMSprop optimizer in the BreastNet-SVM model yields excellent results, achieving high accuracy (98.30%), low miss classification rate (1.70%), high sensitivity (99.74%), and high specificity (96.05%) when the input image size is set to 32 × 32. On the other hand, employing the Adam optimizer leads to a high accuracy rate of 96.55%, a miss classification rate of 3.45%, a sensitivity rate of 95.53%, and a specificity rate of 97.76% for the proposed model. The study also highlights that when utilizing the SGD optimizer, the BreastNet-SVM model achieves peak accuracy of 98.77% at an input image size of 32 × 32, with a miss classification rate of 1.23%, sensitivity of 98.60%, and specificity of 99.03%.

TABLE 2. Comparative evaluation of the BreastNet-SVM model while being trained.

Optimizer	Input image size	Specificity	Sensitivity	Accuracy	Miss Classification rate
RMSprop	16×16	97.43%	90.04%	93.26 %	6.74%
Adam	16×16	96.66%	93.34%	95.02 %	4.98%
SGD	16×16	98.94%	97.93%	98.85 %	1.15%
RMSprop	32×32	96.05%	99.74%	98.30 %	1.70%
Adam	32×32	97.76%	95.53%	96.55 %	3.45%
SGD	32×32	99.03%	98.60%	98.77 %	1.23%
RMSprop	48×48	98.01%	96.99%	97.35 %	2.65%
Adam	48×48	98.32%	98.34%	97.98 %	2.02%
SGD	48×48	99.56%	98.78%	99.24 %	0.76%

The suggested model using RMSprop has a 97.35% accuracy rate and a 2.65% miss classification rate. Moreover, the model exhibits a sensitivity rate of 96.99% and a specificity rate of 98.01% when the input image dimensions are set to 48 × 48. When employing the Adam optimizer, a high accuracy rate of 97.98% is obtained with a low miss classification rate of 2.02%. Additionally, the model demonstrates a high sensitivity rate of 98.34% and a specificity rate of 98.32%. Finally, by utilizing the SGD optimizer, the BreastNet-SVM model achieves a peak accuracy of 99.24%, accompanied by a miss classification rate of 0.76%, a sensitivity rate of 98.78%, and a specificity rate of 99.56%.

Table 3 is a comparison of the validation phase using various optimizers for the proposed BreastNet-SVM model. Three input image sizes (16 × 16, 32 × 32, and 48 × 48) are taken into account by the model during validation. The optimizers used for this analysis are Adam, RMSprop, and SGD.

The performance metrics of the proposed BreastNet-SVM model utilizing the RMSprop optimizer are as follows: accuracy of 87.38%, miss classification rate of 12.62%, sensitivity of 79.49%, and specificity of 99.60% at an input image size of 16 × 16. The Adam optimizer yields an accuracy rate of 95.02%, a miss classification rate of 4.98%, a sensitivity rate of 90.24%, and a specificity rate of 96.34% for the proposed model. When employing the SGD optimizer, the BreastNet-SVM model achieves an optimal accuracy of 93.94% during the validation phase, in addition to a 97.09% sensitivity, a 95.02% specificity, and a 6.06% incidence of miss classification.

The suggested model with RMSprop performs at a high level of accuracy, 95.93%, for a 32 × 32 input picture size, with a low miss classification rate, of 4.07%. Both the

TABLE 3. Comparative evaluation of the suggested BreastNet-SVM model (validation).

Optimizer	Input image size	Specificity	Sensitivity	Accuracy	Miss Classification rate
RMSprop	16×16	99.60 %	79.49 %	87.38 %	12.62%
Adam	16×16	96.34 %	90.24 %	95.02 %	4.98%
SGD	16×16	95.02 %	97.09 %	93.94 %	6.06%
RMSprop	32×32	96.94 %	87.98 %	95.93 %	4.07%
Adam	32×32	96.25 %	94.03 %	92.01 %	7.99%
SGD	32×32	97.64 %	96.04 %	96.03 %	3.97%
RMSprop	48×48	96.94 %	94.11 %	96.56 %	3.44%
Adam	48×48	98.24 %	95.45 %	95.89 %	4.11%
SGD	48×48	99.30 %	97.13 %	99.16 %	0.84%

sensitivity (87.98%) and specificity (96.94%) of the model are above average. The proposed model achieves an accuracy of 92.01 percent, a miss classification rate of 7.99 percent, a sensitivity of 94.03%, and a specificity of 96.25% when optimized using the Adam algorithm. The maximum accuracy of 96.03%, the miss classification rate of 3.97%, the sensitivity of 96.04%, and the specificity of 97.64% are all shown by the model trained using the SGD optimizer.

At an input image size of 48 × 48, the BreastNet-SVM model with RMSprop achieves an accuracy of 96.56%, a miss classification rate of 3.44%, a sensitivity of 94.11%, and a specificity of 96.94%. The accuracy, miss classification rate, sensitivity, and specificity of the Adam optimizers are 95.89%, 4.11%, 95.45%, and 98.24%, respectively. The BreastNet-SVM model, utilizing the SGD optimizer, attains a peak accuracy of 99.16%, with a 0.84% miss classification rate, 97.13% sensitivity, and 99.30% specificity, respectively.

Using the SGD optimizer and a 48 × 48 input image size, the results show that the model performs best. While training the BreastNet-SVM model with the SGD optimizer, the confusion matrix is displayed in Table 4. The model was trained on a dataset of 1880 samples, which were categorized into malignant and benign classes.

Within the study's context, the suggested BreastNet-SVM model underwent training using 960 samples from the benign category. The model's performance was assessed based on its capacity to accurately classify the samples. Among the 960 samples, the model correctly predicted 956 samples, while 4 samples were misclassified. In the case of malignant samples, the BreastNet-SVM model was trained using a dataset of 920 samples. The model accurately predicted 909 samples, while 11 samples were inaccurately classified. The best accuracy was achieved by using the SGD optimizer, and the confusion matrix is presented in Table 5 from the validation phase of the BreastNet-SVM model.

TABLE 4. The BreastNet-SVM model's best confusion matrix (training).

Actual Class	Predicted class	
	Benign	Malignant
Benign	956	4
Malignant	11	909

TABLE 5. The BreastNet-SVM model's best confusion matrix (validation).

Actual Class	Predicted class	
	Benign	Malignant
Benign	220	2
Malignant	7	251

For the validation process, a sample size of 480 was used to assess the proposed model. This set of 480 samples was subsequently divided into two distinct categories: malignant and benign.

The proposed BreastNet-SVM model exhibits a high level of accuracy in predicting benign cases, with 220 out of 222 samples correctly classified and only 2 samples being misclassified during the validation process. A total of 258 samples were used in the process of validating the proposed model in the malignant case. The BreastNet-SVM model under consideration accurately predicted 251 samples while incorrectly predicting 7 samples. Figure 3 displays the outcomes of the modified AlexNet model proposed for detecting breast cancer, encompassing both benign and malignant results. The BreastNet-SVM model's accurate classification of benign cases as benign is evidenced by its correct prediction of the first three images, which are therefore classified as true negatives. The present study exhibits three images that have been identified as false positives, as the BreastNet-SVM model has erroneously classified them as malignant despite their benign nature. The initial trio of visuals pertaining to malignant tissue is presented as erroneous negatives, and the BreastNet-SVM framework posits that they are indicative of benignity, despite their actual malignancy. The last trio of images is presented as authentic positive results, and the BreastNet-SVM model under consideration anticipates their malignancy status with accuracy.

A comparative analysis between the suggested BreastNet-SVM model and other contemporary cutting-edge approaches is showcased in Table 6. Previous research efforts employed various convolutional neural network (CNN) models to

TABLE 6. BreastNet-SVM vs. current methods.

Author	Method	Dataset	Year	Accuracy (%)
Khan et al. [13]	GoogLeNet, VGGNet, and ResNet	LRH hospital Peshawar, Pakistan	2019	97.52
Elbashir et al. [20]	RNA-Seq-based compact CNN	Pan-Cancer Atlas gene expression data	2019	98.76
Moon et al. [12]	Ensemble (WA)	BUSI	2020	91.10
Zuluaga-Gomez et al. [2]	ResNet, SeResNet, VGG16, Inception, InceptionResNetV2, and Xception	DMR-IR	2020	94.0
Toğaçar et al. [18]	convolutional neural network (CNN) that includes an attention module and hypercolumn technique.	BreakHis	2020	95.03
Hadush et al. [19]	Designed CNN architecture with RPN and ROI pooling from faster R-CNN for feature extraction.	St.Gebriel Hospital	2020	91.86
Saber et al. [14]	Inception-V2 ResNet, VGG-16, VGG-19, ResNet50, and Inception V3	MIAS	2021	98.96
Sivanandan et al. [15]	StepNet	domain-specific dataset of ultrasound breast tumor images	2021	91.67
Wang et al. [16]	Boosted EfficientNet model	Rectified Patch Camelyon (RPCam)	2021	96.50
Hekal et al. [17]	AlexNet and ResNet-50	CBIS-DDSM ROI	2021	93.2
Jayandhi et al. [7]	VGG-SVM	MIAS	2022	98.67
Maqsood et al. [10]	Transferable texture convolutional neural network (TTCNN)	DDSM	2022	97.49
Tavakoli et al. [11]	Architected block-based CNN	MIAS	2023	94.68
Proposed BreastNet-SVM	Modified CNN and SVM	DDSM	2023	99.16%

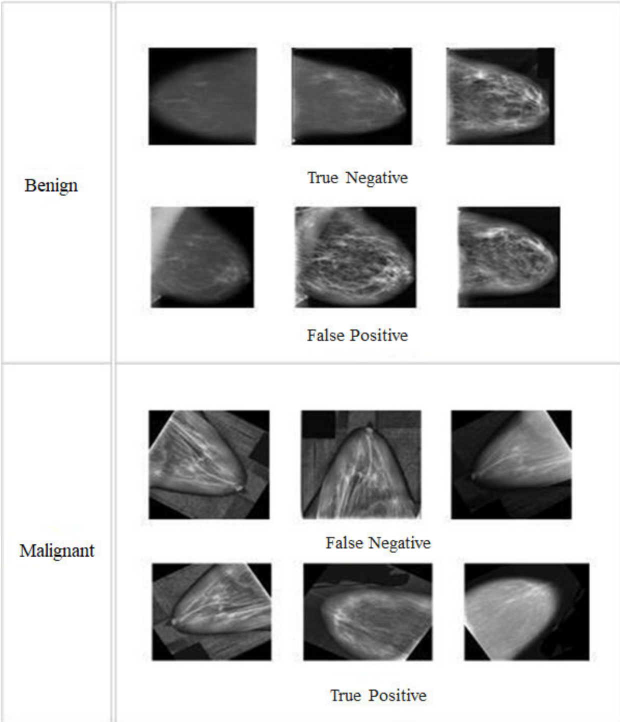

FIGURE 3. The BreastNet-SVM model's benign and malignant breast tissues.

examine openly available datasets of breast mammogram diagnosis, all aimed at identifying cases of breast cancer. The results for specificity, sensitivity, and recall show that the proposed BreastNet-SVM model is more accurate and efficient than its predecessors.

V. CONCLUSION

BreastNet-SVM, a novel research endeavor, introduces a pioneering method for precisely segmenting and classifying breast tissues in mammograms. This innovative approach modifies the AlexNet architecture. Classification is accomplished through the utilization of a support vector machine algorithm. The validation and training process of the model involves three different image dimensions. To optimize performance, the model employs the Adam, RMSprop, and SGD algorithms. Remarkably, with the SGD optimizer, the BreastNet-SVM model achieves an exceptional accuracy of 99.16% on 48×48 images. Experimental analysis, conducted on the publicly available DDSM dataset, showcases a minimal miss classification rate of 0.84%, an impressive sensitivity of 97.13%, a remarkable specificity of 99.30%, and the highest precision among comparable studies.

VI. LIMITATIONS AND FUTURE WORK

When considering the BreastNet-SVM model, effective classification of breast cancer as benign or malignant can be achieved. BreastNet-SVM has shown improved accuracy in the identification of both malignant and benign diseases by adopting the modified AlexNet architecture. It's vital to recognize that the suggested framework has certain inherent limitations. These limitations encompass the model's reliance on a single dataset for both training and validation purposes, the adoption of three different sizes of mammography images, and the utilization of three specific optimizers.

REFERENCES

[1] S. Sadhukhan, N. Upadhyay, and P. Chakraborty, "Breast cancer diagnosis using image processing and machine learning," in *Emerging Technology in Modelling and Graphics* (Advances in Intelligent Systems and Computing), J. K. Mandal and D. Bhattacharya, Eds. Singapore: Springer, 2020, pp. 113–127, doi: 10.1007/978-981-13-7403-6_12.

[2] J. Zuluaga-Gomez, Z. Al Masry, K. Benaggoune, S. Meraghni, and N. Zerhouni, "A CNN-based methodology for breast cancer diagnosis using thermal images," *Comput. Methods Biomech. Biomed. Eng. Imag. Visualizat.*, vol. 9, no. 2, pp. 131–145, Mar. 2021, doi: 10.1080/21681163.2020.1824685.

[3] K. Ganesan, U. R. Acharya, C. K. Chua, L. C. Min, K. T. Abraham, and K.-H. Ng, "Computer-aided breast cancer detection using mammograms: A review," *IEEE Rev. Biomed. Eng.*, vol. 6, pp. 77–98, 2013, doi: 10.1109/RBME.2012.2232289.

[4] J. Escorcia-Gutierrez, R. F. Mansour, K. Beleño, J. Jiménez-Cabas, M. Pérez, N. Madera, and K. Velasquez, "Automated deep learning empowered breast cancer diagnosis using biomedical mammogram images," *Comput. Mater. Contin.*, vol. 71, no. 3, pp. 4221–4235, 2022, doi: 10.32604/cmc.2022.022322.

[5] E. H. Houssein, M. M. Emam, A. A. Ali, and P. N. Suganthan, "Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review," *Expert Syst. Appl.*, vol. 167, Apr. 2021, Art. no. 114161, doi: 10.1016/j.eswa.2020.114161.

[6] D. A. Ragab, M. Sharkas, S. Marshall, and J. Ren, "Breast cancer detection using deep convolutional neural networks and support vector machines," *PeerJ*, vol. 7, p. e6201, Jan. 2019, doi: 10.7717/peerj.6201.

[7] G. Jayandhi, J. S. L. Jasmine, and S. M. Joans, "Mammogram learning system for breast cancer diagnosis using deep learning SVM," *Comput. Syst. Sci. Eng.*, vol. 40, no. 2, pp. 491–503, 2022.

[8] D. Albashish, R. Al-Sayyed, A. Abdullah, M. H. Ryalat, and N. A. Almansour, "Deep CNN model based on VGG16 for breast cancer classification," in *Proc. Int. Conf. Inf. Technol. (ICIT)*, Jul. 2021, pp. 805–810, doi: 10.1109/ICIT52682.2021.9491631.

[9] Y. J. Tan, K. S. Sim, and F. F. Ting, "Breast cancer detection using convolutional neural networks for mammogram imaging system," in *Proc. Int. Conf. Robot., Autom. Sci. (ICORAS)*, Nov. 2017, pp. 1–5, doi: 10.1109/ICORAS.2017.8308076.

[10] S. Maqsood, R. Damaševičius, and R. Maskeliūnas, "TTCNN: A breast cancer detection and classification towards computer-aided diagnosis using digital mammography in early stages," *Appl. Sci.*, vol. 12, no. 7, p. 3273, Mar. 2022, doi: 10.3390/app12073273.

[11] N. Tavakoli, M. Karimi, A. Norouzi, N. Karimi, S. Samavi, and S. M. R. Soroushmehr, "Detection of abnormalities in mammograms using deep features," *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 5, pp. 5355–5367, May 2023, doi: 10.1007/s12652-019-01639-x.

[12] W. K. Moon, Y.-W. Lee, H.-H. Ke, S. H. Lee, C.-S. Huang, and R.-F. Chang, "Computer-aided diagnosis of breast ultrasound images using ensemble learning from convolutional neural networks," *Comput. Methods Programs Biomed.*, vol. 190, Jul. 2020, Art. no. 105361, doi: 10.1016/j.cmpb.2020.105361.

[13] S. Khan, N. Islam, Z. Jan, I. U. Din, and J. J. P. C. Rodrigues, "A novel deep learning based framework for the detection and classification of breast cancer using transfer learning," *Pattern Recognit. Lett.*, vol. 125, pp. 1–6, Jul. 2019, doi: 10.1016/j.patrec.2019.03.022.

[14] A. Saber, M. Sakr, O. M. Abo-Seida, A. Keshk, and H. Chen, "A novel deep-learning model for automatic detection and classification of breast cancer using the transfer-learning technique," *IEEE Access*, vol. 9, pp. 71194–71209, 2021, doi: 10.1109/ACCESS.2021.3079204.

[15] R. Sivanandan and J. Jayakumari, "A new CNN architecture for efficient classification of ultrasound breast tumor images with activation map clustering based prediction validation," *Med. Biol. Eng. Comput.*, vol. 59, no. 4, pp. 957–968, Apr. 2021, doi: 10.1007/s11517-021-02357-3.

[16] J. Wang, Q. Liu, H. Xie, Z. Yang, and H. Zhou, "Boosted EfficientNet: Detection of lymph node metastases in breast cancer using convolutional neural networks," *Cancers*, vol. 13, no. 4, p. 661, Feb. 2021, doi: 10.3390/cancers13040661.

[17] A. A. Hekal, A. Elnakib, and H. E.-D. Moustafa, "Automated early breast cancer detection and classification system," *Signal, Image Video Process.*, vol. 15, no. 7, pp. 1497–1505, Oct. 2021, doi: 10.1007/s11760-021-01882-w.

[18] M. Toğaçar, K. B. Özkurt, B. Ergen, and Z. Cömert, "BreastNet: A novel convolutional neural network model through histopathological images for the diagnosis of breast cancer," *Phys. A, Stat. Mech. Appl.*, vol. 545, May 2020, Art. no. 123592, doi: 10.1016/j.physa.2019.123592.

[19] S. Hadush, Y. Girmay, A. Sinamo, and G. Hagos, "Breast cancer detection using convolutional neural networks," 2020, *arXiv:2003.07911*.

[20] M. K. Elbashir, M. Ezz, M. Mohammed, and S. S. Saloum, "Lightweight convolutional neural network for breast cancer classification using RNA-seq gene expression data," *IEEE Access*, vol. 7, pp. 185338–185348, 2019, doi: 10.1109/ACCESS.2019.2960722.

[21] S. Srihari. *The Convolution Operation*. Accessed: Jun. 15, 2023. [Online]. Available: https://cedar.buffalo.edu/~srihari/CSE676/9.1%20ConvOperation.pdf

[22] J. H. Sci, "Relu deep neural networks and linear finite elements," *J. Comput. Math.*, vol. 38, no. 3, pp. 502–527, Jun. 2020, doi: 10.4208/jcm.1901-m2018-0160.

[23] (2021). *EE212 Mathematical Foundations for Machine Learning and Data Science*. Accessed: Jun. 15, 2023. [Online]. Available: https://www.zubairkhalid.org/ee212_2021.html

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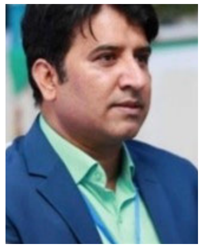

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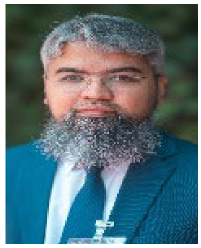

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