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Transfer Learning based Breast Cancer Classification via Deep Convolutional Neural Network

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Abstract: Breast cancer is a leading cause of death among women, and the subjectivity of human visual perception and lack of automated detection methods can lead to misclassification of breast cancer images. In this study, a breast cancer classification model using a Convolutional Neural Network (CNN) deep learning algorithm was proposed. The model demonstrated high accuracy in classifying breast images as benign or malignant, with a classification accuracy of 97.1%. The model was also able to run on low computational resources. The study used a dataset of 2009 breast images labeled by two radiologists and included six scenarios based on different hyperparameters, augmentation values, pretrained models, and models built from scratch. While the performance of the proposed model was promising, further improvement may be achieved by using a larger breast image dataset and a machine with more powerful GPU hardware.

Index Terms: Deep Learning, Convolutional Neural Network, Breast Cancer Classification, Benign, Malignant.

1. Introduction

Cancer is a significant public health concern in countries in Sub-Saharan Africa, including Ethiopia [1]. Breast cancer can be identified through clinical breast examination, but this method is not always reliable and can be difficult to use to detect abnormal areas that cannot be felt but can be seen on a mammogram or ultrasound. Mammography is a common radiological approach for detecting breast cancer, especially in the early stages before it has spread. The standard views taken during a mammogram include the Craniocaudal (CC) and Mediolateral Oblique (MLO) views, with the CC view being taken from a horizontally compressed breast and the MLO view providing the best views of the side of the breasts [2]. Figure 1 shows the CC and MLO views of the right and left breasts, respectively.

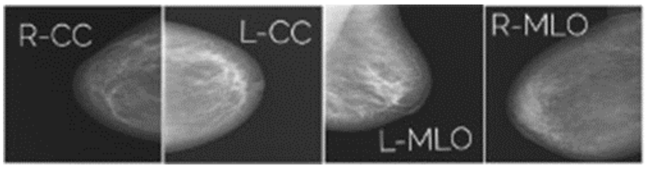

Fig. 1. Breast image views

Cancer is a disease characterized by the uncontrolled growth of cells, tissues, or organs that can form a tumor. There are many different types of cancer, including breast cancer, which occurs when cells in the breast grow out of control and become abnormal, potentially spreading to other tissues and forming a tumor that may be visible on x-rays or palpable as a lump. While breast cancer primarily affects women, it can also occur in men. Benign breast tumors are non-cancerous and do not spread to other parts of the body, while malignant tumors can spread to other areas of the body and be more dangerous [3]. In Ethiopia, a study estimates that cancer accounts for 5.8% of total national mortality [4]. In Addis Ababa, the annual incidence of cancer is estimated to be 60,960 cases, with an annual mortality rate of over 44,000, and women make up approximately two-thirds of all cancer deaths, with breast cancer being the leading cause of mortality among women of all ages [5].

Cancer is typically treated with medical or radiation therapy within the healthcare system, although some individuals may seek treatment abroad. However, many developing countries lack sufficient cancer treatment capacity and certain cancer treatments may not be readily available. According to the Black Lion Specialized Hospital in Addis Ababa, Ethiopia [1], approximately 80% of cancer patients are diagnosed in the later stages of their disease when effective treatment is no longer possible. This is often due to a lack of awareness about cancer symptoms and signs, insufficient screening, a lack of diagnostic facilities, and poor coordination of referrals. In this study, data augmentation, transfer learning using pretrained models, and hyperparameter values were explored in order to develop a Convolutional Neural Network (CNN) model capable of accurately classifying breast cancer using medical images.

Mammography is a widely used method for detecting breast cancer in its early stages, particularly in asymptomatic women. However, accurately diagnosing breast cancer can be difficult because it is not a single disease, but rather a group of several different diseases that can present differently in different people. In these cases, deep learning approaches can help radiologists detect and classify tumors by analyzing diagnostic images and providing real-time information about the presence of the disease.

Cancer classification is further complicated by the fact that each case of cancer is unique and may be affected by factors such as the individual's breast tissue and any previous surgeries. Comprehensive diagnosis and treatment can be costly and time-consuming, but are necessary to effectively address these challenges.

This study made the following contributions:

1. Collection and preparation of breast image data from a Korean hospital in Ethiopia.
2. Experimentation with eight different data augmentation parameters to increase the data size and improve performance.
3. Development of a breast cancer classification model using a deep CNN algorithm, with experimentation in various scenarios.
4. Improved performance of the proposed model through the use of data augmentation, as the eight parameters used artificially increased the data and allowed the neural network to learn more features.

2. Literature Survey

The section describes the work of various scholars on breast cancer classification and detection using various approaches, methods, and algorithms.

Rashed et al. [7] examined the use of traditional x-ray mammography for breast cancer screening. They noted that this method can be challenging for detecting small abnormalities and that variations in breast tissue can impact the accuracy of diagnoses made using handcrafted features. To address these issues, the authors proposed a deep learning approach inspired by the U-net architecture. This approach was tested using the Curated Breast Imaging Subset of DDSM (CBIS-DDSM) dataset, which included 6,671 mammography images representing normal, benign, and malignant cases. The researchers found that the proposed method, using pretrained models AlexNet, VGGNet, and GoogleNet, achieved an accuracy of 94.31% for micro-classification and 95.01% for masses. Overall, their work highlights the potential of this new technology to improve decision-making in mammography.

Geras et al. [8] argued that deep learning approaches for natural and medical images have employed similar techniques, but there are key differences between the two types of images that must be taken into account. While the fine details of medical images are crucial for accurate breast cancer identification, this is not the case for natural images. Moreover, the network architectures developed for natural images often downscale the input to reduce memory requirements, potentially obscuring important details in medical images. To address these issues, the authors developed a multi-view CNN that can process a series of high-quality medical images simultaneously. They tested their model using a dataset from the New York City metropolitan area, dividing the data into training, validation, and test sets of

80%, 10%, and 10%, respectively. The results of the study indicated that the model's performance could be improved by gathering more data.

Kassani et al. [9] presented an automatic classification method for breast histology images using an ensemble model that leveraged the pretrained CNN architectures of VGG19, MobileNet, and DenseNet for feature extraction and representation. This approach was compared to traditional machine learning methods, which typically require manual input from domain experts for tasks such as image annotation and feature extraction [10]. The authors also modified the K-means algorithm to extract regions of interest from local and public datasets [11]. The study included a total of 320 images, 112 of which were abnormal and 208 of which were normal. These images were classified using a Support Vector Machine (SVM) and an equal number of images from both the public and local databases. The proposed model achieved an accuracy of 96.88% in the classification of the images.

Ragab et al. [12] employed a combination of threshold and region-based segmentation techniques to manually define the region of interest in their study. They then used a DCNN for feature extraction and fine-tuned AlexNet to classify the images into two classes. An SVM was also used to improve the classification accuracy. The researchers conducted their experiments using the open-source Curated Breast Imaging Subset of DDSM (CBIS-DDSM) dataset.

Table 1. Related Works

References	Local Dataset	DS	Aug	CNN	PM	Accuracy
[18]	–	✓	✓	✓	✓	96%
[19]	–	–	✓	✓	✓	97%
[7]	–	✓	–	✓	✓	95.01%
[8]	–	✓	✓	✓	✓	86.5%
[20]	–	–	–	–	–	91.04%
[12]	–	✓	✓	✓	✓	87.2%
[21]	NA	–	–	–	–	93%
[22]	–	–	–	–	–	97%
[11]	✓	–	–	–	–	96.88%
Proposed work	✓	✓	✓	✓	✓	97.1%

Where: DS= Data Size, Aug=Augmentation, and PM=Pretrained Model

The researcher use machine learning and transfer learning to for COVID and TB detection [11-13]. Images are used for brain tumor detection using deep learning[14]. The data augmentation is techniques are clearly discussed by authors [15,16].

3. Proposed Methodology

Several researchers have suggested that a CNN is a promising approach for tasks such as image classification. One reason for this is that, unlike traditional machine learning algorithms, a CNN can automatically handle tasks such as feature extraction and other preprocessing. This capability makes it possible for radiologists to use raw medical images from digital breast tomosynthesis, digital mammography, and ultrasound imaging modalities to diagnose various diseases. The system architecture of the proposed model is shown in Figure 2.

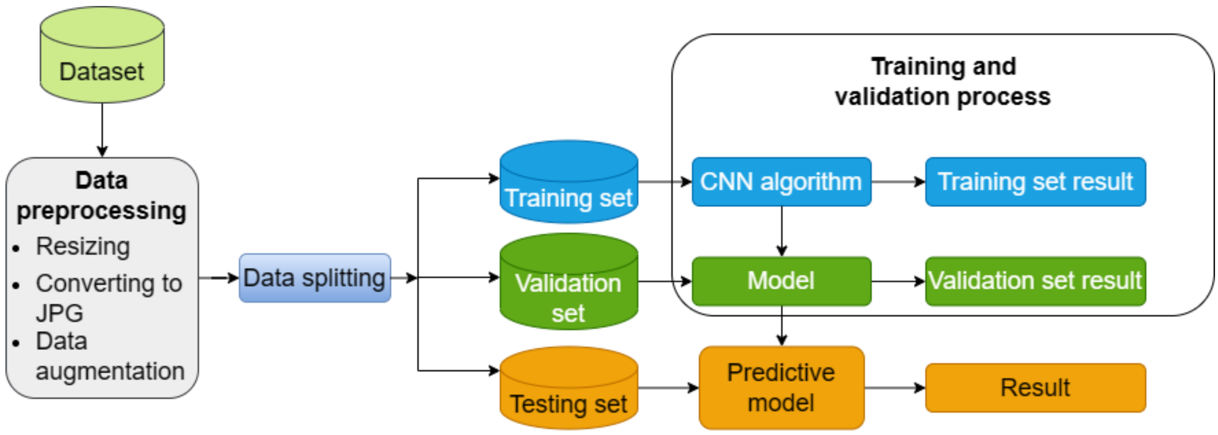

Fig. 2. Overall system architecture

In this study, a total of 2009 mammogram images were collected, including 1204 malignant and 805 benign images. These images were labeled by two radiologists from a Korean hospital, Addis Ababa, Ethiopia. The dataset was then divided into a training set and a testing set to build the proposed model. Before the CNN algorithm was used for feature extraction and classification, a series of data preparation processes were applied to the raw mammography images. These processes included data preprocessing, cleaning, reduction, and augmentation, all of which were carried out in the training phase. Once the data had been prepared, the deep CNN algorithm was used to perform feature extraction and classification tasks on the mammography images. To determine which model performs well and achieves good results, the study use validation sets. After training the model, the study evaluate it as described in Section III-E. Then, the study test the model using a test set to see if it can accurately predict whether a breast image is benign or malignant.

3.1. Deep CNN Algorithm

One of the challenges faced by researchers in the field of CNNs (Convolutional Neural Networks) is the large number of parameters these models have, which necessitate the use of a large amount of data for training and testing, as well as powerful computational resources. To mitigate this challenge, researchers can employ techniques such as data augmentation and transfer learning. The CNN algorithm consists of four main components: the convolutional (conv) layer, pooling layer, activation function (AF), and fully connected (FC) layer.

3.2. Conv Layer

There are 5 Conv layers in the proposed model. The first Conv layer of the model filters the 150×150 input image using 32 filters. The number of parameters of the proposed model is computed using Equation 1.

$$(FH * \mathrm{FW} * \mathrm{IIC} + 1) * NF \tag{1}$$

Where: $FH =$ Filter Height, $\mathrm{FW} =$ Filter Width, IIC = Input Image Channels, and NF =Number of Filters.
The Conv operation of two functions f and d over $[-\infty, \infty]$ mathematically expressed as [23]

$$(f * \mathrm{d})(t) \triangleq \int_{-\infty}^{\infty} f(t)\, g(t) dt \tag{2}$$

Where: $(f * \mathrm{d})(t)$ represents the conv of two functions f and d.

3.3. Pooling Layer

After every five convolutional layers, there are five max-pooling layers in the proposed model. In this layer, there are no learnable parameter functions because it has zero parameters. The key role of pooling is to downsample the spatial dimension of the input volume of the mammogram images. Mathematically, max-pooling is calculated using equation 3.

$$\left(\left(\left((IH - PH)/stride\right) + 1\right), \left(\left((IH - PH)/stride\right) + 1\right), Filter\right) \tag{3}$$

Where: IH = Image Height, and PH = Pooling Height

3.4. Activation Function

This is one of the components of CNN which is used to solve varieties of complex problems like image classification or detection. Most activation functions add non-linearity properties which solve the drawback of early neural networks. Finally, the activation function determines the final output of a neuron [24,25].

3.5. Fc Layer

The proposed model has incorporated two fully-connected layers. The first fully-connected layer includes 256 neurons and the second fully-connected layer, which serves as the model's output layer, includes 2 neurons. The first fully-connected layer processes the output from the fifth convolutional layer and the flattening layer.

3.6. Transfer Learning

Transfer learning, a method in which pretrained parameters are utilized to address various computer vision tasks, is often employed to improve the performance of deep learning algorithms on these tasks (e.g. [26-28]). This technique allows the weights of a deep learning model trained on a large dataset to be transferred and applied to related tasks.

3.7. Feature Extraction

Feature extraction is a key step in image classification, particularly when using a CNN. The algorithm is able to automatically extract features from images without human input, making them a useful tool for this task. In this study, we used a CNN to extract features from images, which were then used to classify them as either benign or malignant. The feature extraction process is depicted in Figure 3.

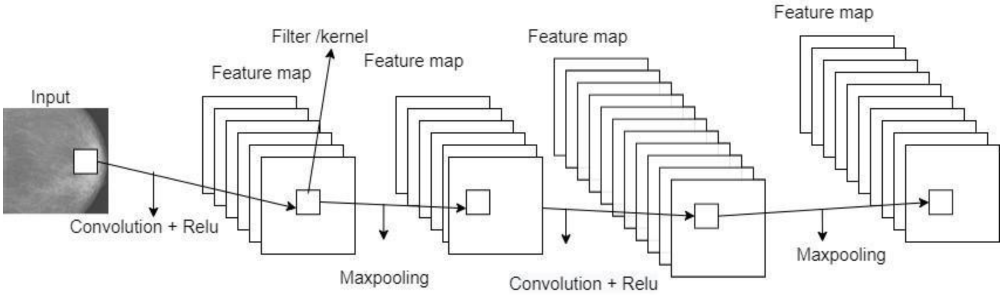

Fig. 3. Feature extraction of the proposed model

4. Experiment

4.1. Dataset

The original dataset for this study consisted of 2009 breast images, which were divided into two categories: benign and malignant breast cancers. The dataset included 1204 images of malignant breast cancer and 805 images of benign breast cancer. These images were labeled by four radiologists working at a hospital in Addis Ababa, Ethiopia. Figure 4 shows the sample dataset used in this study. Data augmentation techniques were applied to this dataset during the preparation process. The sample dataset of the study is depicted in Figure 4.

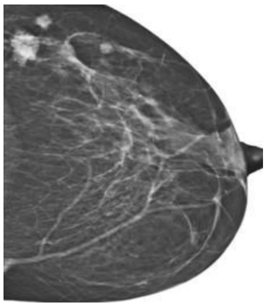

Fig. 4. Sample breast image

4.2. Experimental Scenarios

In order to identify the best breast cancer classification model, the study conducted experiments according to six different scenarios. Each scenario varied in terms of the values of its hyperparameters, the data partitioning method used, and the type of pretrained model (InceptionV3, VGG16, ResNet50, or VGG19) or proposed model employed. The hyperparameters explored included the activation function, learning rate, epoch, batch size, loss function, optimization algorithm, and cross-entropy [29]. The randomly chosen values for the hyperparameters are shown in Table 4, and a summary of the scenarios is presented in Table 3.

Table 2. Experimental scenarios

Scenarios	Cases	Accuracy	Loss
Scenario1	Using 90%-10% data splitting	96%	0.1019
Scenario2	Using 80%-20% data splitting	97.01%	0.0755
Scenario3	Using 70%-30% data splitting	94.02%	0.1754
Scenario4	Using 80%-20% data splitting along with 0.0001 LR	90.05	0.2583
Scenario5	Using RMSprop as an optimization algorithm	95.52%	0.889
Scenario6	Using last layer activation function Softmax	91.04%	0.230

4.3. Hyperparameter Settings

Proper selection of hyperparameter values can enhance the learning process of a neural network. In this paper, the study considered the following hyperparameters: loss function, number of epochs, optimization algorithm, learning rate, activation function, and batch size. The study employed the random search method to determine the optimal hyperparameter values for the proposed model, as it requires fewer computational resources compared to other methods such as grid search.

LR: This is the most significant hyperparameter for optimizing the neural network [30]. It has a value between 0 and 1.

Optimization Algorithm: This is the main hyperparameter that allows the model to learn faster and produce better results. Furthermore, optimization approaches were used to update the weights for each batch to find global minimum requirements. The proposed model employs a gradient descent optimization algorithm to reduce error rates, and the

Stochastic Gradient Descent (SGD) approach is used to update the weights for each training set [31]. In this study, Adam and RMSprop optimization algorithms experimented by adjusting the LR to 0.001 and 0.0001.

Loss Function: Binary cross-entropy was used to build a proposed model. Because the loss function is recommended for binary classification problems.

Activation Function: This is a function that transforms the input signals into output signals [24] [25]. In the proposed model, Sigmoid and Softmax have experimented with the last layer AF. The Sigmoid activation function gives a better result. The reason behind using the Sigmoid activation function in the last layer is it usually scores better for a problem like binary classification. The two activation functions are mostly used in the final layer of a neural network-based classifier.

Number of Epochs: This is the number of iterations trained by the neural network in the model [32,33]. The proposed model was trained in our experiment using different epochs starting from 5 to 80. The result achieved using a too-large or too-small number of the epoch is not promising. However, by conducting several experiments the optimal number of an epoch that achieves a better result is 20.

Batch Size: This is the number of input data that is transferred through the network at once. The default batch size values are 128, 64, and 32. Batch size values of 128, 64, and 32 have been experimented. Among those, a batch size of 32 scores the best performance while building the proposed model.

Table 3. Hyperparameter of the experimentation

Hyperparameters	Value
Epoch	20
Activation Function	Sigmoid
Loss Function	Binary cross-entropy
Optimization algorithm	Adam
Learning rate	0.001
Batch Size	32
Drop out	0.4

Augmentation Parameters: One of the requirements for deep learning techniques is a large quantity of training data. This is because a larger dataset allows the neural network to learn more complex features and avoid overfitting [32]. Additionally, the performance of a deep learning model is often dependent on the number of training images used. The study applied eight augmentation parameters to 1607 breast images in the training dataset. The augmentation parameters used in the experiments are shown in Table 5. By augmenting the training data, the study aimed to increase the overall amount of data and potentially improve the performance of the model.

Table 4.Augmentation parameter of the experimentation

Parameter	Value
Rescale	1./255
Horizontal Flip	True
Rotation range	40
Shear Range	0.3
Width Shift Range	0.2
Height Shift Range	0.2
Zoom Range	0.1
Flip mode	Nearest

5. Results and Discussions

In this study, four different pretrained models (VGG16, VGG19, Inception-V3, and ResNET50) and the proposed model were experimented with in six different scenarios. The results of the experiments showed that the VGG16 model had an accuracy of 80.60%, while the VGG19 model had a lower accuracy of 72.64%. The InceptionV3 model performed better, with an accuracy of 91.04%. The ResNet50 model had the lowest accuracy of 59.70%. The proposed model had an accuracy of 97.1%, which was satisfactory. The performance of the proposed model is shown in Table 6, and the training and validation graph is depicted in Figure 5.

Table 5. The proposed model classification metrics

	Precision	Recall	F1-Score	Support
Benign	0.96	0.98	0.97	81
Malignant	0.98	0.98	0.98	120
Micro avg	0.97	0.98	0.98	201
Macro avg	0.97	0.98	0.97	201
Weighted avg	0.97	0.98	0.98	201
Samples avg	0.98	0.98	0.98	201

The training and validation curves of a deep learning model demonstrate whether the model is overfitting or not. The proposed model's training and validation accuracy are presented in Figure 5. As the Figure depicted the training and validation graph gaps are small, indicating that the model is not overfitted.

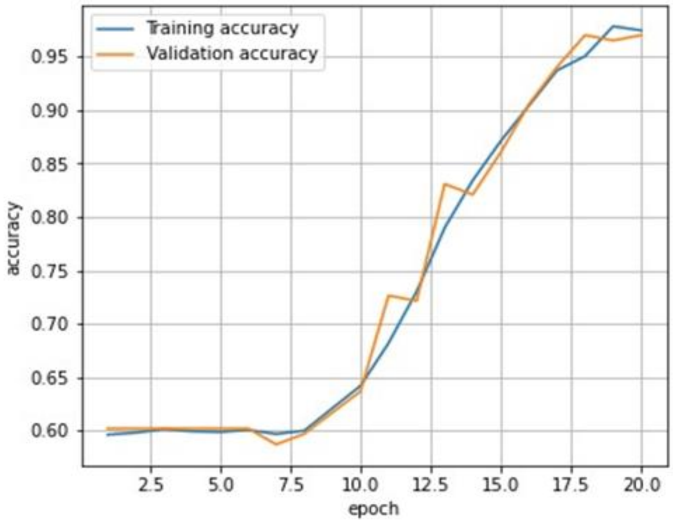

Fig. 5. Training and validation accuracy

The proposed model is a convolutional neural network (CNN) that has a relatively small number of parameters compared to other pretrained models, such as VGG19 and VGG16, which have 138 million parameters each. This small number of parameters helps to prevent overfitting and enables the model to run on fewer computational resources. The proposed model has 5 convolutional layers, 2 fully connected layers, and uses the rectified linear unit (ReLU) activation function to introduce non-linearity during training. Dropout is added after the first fully connected layer to further prevent overfitting. Overall, the proposed model architecture has been carefully designed and optimized through a series of experiments on various parameters, such as the convolutional and pooling layers and the activation function. Figure 6 presents a visual representation of the proposed model architecture.

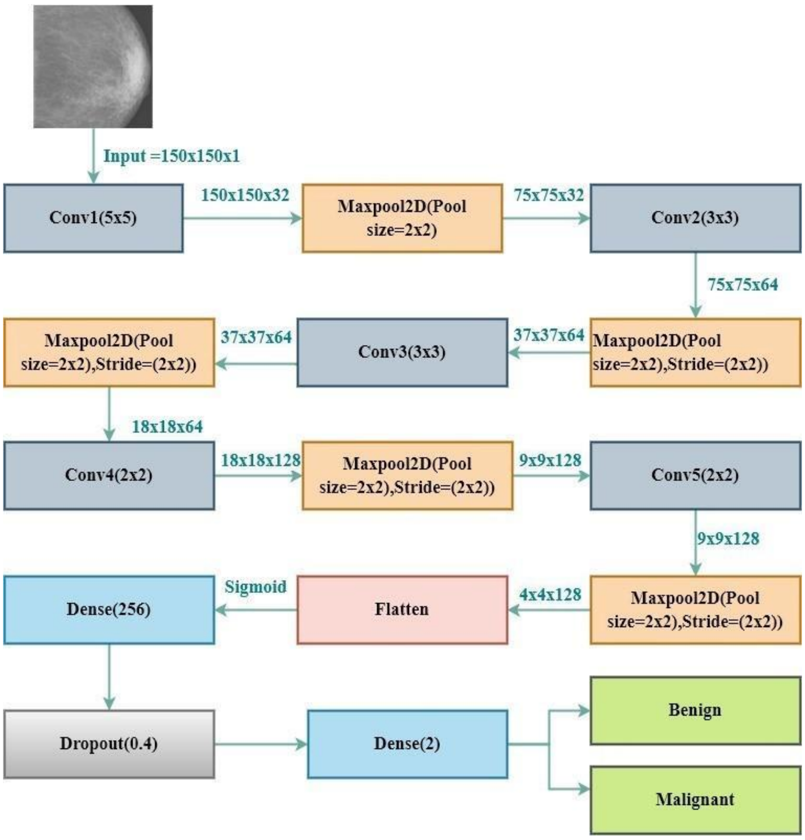

Fig. 6. The proposed CNN architecture

Table 6. Proposed model values

Layers		*FS*	*DS*	*Stri*	*Parameters*	*OS*
I	Image	-	-	-	0	150×150×1
1	C + r	5×5	32		832	150x150x32
	MP	2x2	-	2x2	0	75x75x32
2	C + r	3×3	64		18496	75x75x64
	MP	2×2	-	2x2	0	37x37x64
3	C + r	3×3	64		36928	37x37x64
	MP	2×2		2x2	0	18x18x64
4	C + r	2x2	128		32896	18x18x128
	MP	2×2	-	2x2	0	9 x9 x128
5	C + r	2x2	128		65664	9x9x128
	MP	2x2		2x2	0	4x4x128
	Flatten	-	-	-	0	2048
6	FC + r	-	256	-	524544	256
	D	-	-	-	0	256
7	Output	FC+Sig	2		514	2
Total					679,874	

Where: I=Input, r=relu, D=Dropout, Stri=Stride, FS=Filter ize, C=conv2D, MP=MaxPool2D, DS=Depth Size, Sig= Sigmoid and OS=Output Size

As depicted in Table 8, the proposed model classifies the breast images as ’Benign’ and ’Malignant’ with an accuracy of 97.01% and a loss value of 0.0755. Additionally, the experiment conducted was interesting in the way that the InceptionV3 pretrained model classifies a given image as ’Benign’ and ’Malignant’ with an accuracy of 91.04% and 0.2837 loss value, which is better than other pretrained models. In general, the experimentation found out the proposed model not only performed with good accuracy but also runs with minimal computational resources.

Table 7. Summary of models performance

Models	Accuracy	Loss
VGG16	80.60%	0.4186
VGG19	72.64%	0.5964
InceptionV3	91.04%	0.2837
ResNet50	59.70%	0.673
Proposed Model	**97.01%**	**0.0755**

6. Conclusion

Breast cancer is a significant health concern in Ethiopia, where it is often detected at advanced stages and patients may receive inadequate treatment. Accurate classification of breast images is crucial for early diagnosis and effective treatment, but this can be challenging due to various factors such as abnormalities, misinterpretation of images, and the subjective nature of human perception. To address this issue, a number of deep learning (CNN)-based pretrained models, including VGG16, VGG19, InceptionV3, ResNET50, and a model built from scratch, were evaluated. The proposed model, which utilizes a deep learning approach, was able to accurately classify breast images as benign or malignant with a high level of accuracy. In fact, the proposed model achieved a score of 97.01% accuracy, outperforming the performance of the pretrained models in six specific cases.

The experiments conducted have successfully demonstrated the accuracy of the proposed CNN model in classifying breast images as benign or malignant. Not only did the model perform well in this task, it also required minimal computational resources compared to other deep learning pretrained algorithms. These promising results suggest that further improvement of the model may be possible by training it on a larger breast image dataset and using a high computation machine with a graphics processing unit (GPU). Overall, the proposed CNN model shows great potential for accurately classifying breast images and could potentially play a vital role in improving breast cancerdiagnosis and treatment in Ethiopia and beyond.

References

[1] MahletKifle et al., “Disease prevention and control directorate,” FEDERAL MINISTRY OF HEALTH ETHIOPIA, 2020. [Online]. Available: https://www.iccp-portal.org/sites/default/files/plans. Accessed on: April 10, 2020.

[2] N. Saffari, H. A. Rashwan, M. Abdel-Nasser, V. Kumar Singh, M. Arenas, E. Mangina, B. Herrera, and D. Puig, “Fully automated breast density segmentation and classification using deep learning,” Diagnostics, vol. 10, no. 11, p. 988, 2020.

[3] Cancer.org, “How common is breast cancer?” American Cancer Society, 2022. [Online]. Available: https://www.cancer.org/cancer/breast-cancer/.Accessed on: April 1, 2020.

[4] A. M. T. W. Abate SM, Yilma Z, “Trends of breast cancer in ethiopia,” Int J Cancer Res Mol Mech, vol. 2(1), 2016.

[5] R. Dhivya and R. Dharani, “Survey on breast cancer detection using neural networks,” Forest, vol. 650, pp. 96–777, 2019.

[6] N. M. S. H. R. E. H. M. A. M. L. M. B. K. D. B. E. P. R . S.E. A. Monticciolo, D. L., “Breast cancer screening for average-risk women: Recommendations from the acr commission on breast imaging,” Journal of the American College of Radiology : JACR, vol. 14, no. 9, p. 1137–1143, 2017.

[7] E. Rashed and M. S. A. El Seoud, “Deep learning approach for breast cancer diagnosis,” in Proceedings of the 2019 8th International Conference on Software and Information Engineering, 2019, pp. 243–247.

[8] K. J. Geras, S. Wolfson, Y. Shen, N. Wu, S. Kim, E. Kim, L. Heacock, U. Parikh, L. Moy, and K. Cho, “High-resolution breast cancer screening with multi-view deep convolutional neural networks,” arXiv preprint arXiv:1703.07047, 2017.

[9] S. H. Kassani, P. H. Kassani, M. J. Wesolowski, K. A. Schneider, and R. Deters, “Classification of histopathological biopsy images using ensemble of deep learning networks,” arXiv preprint arXiv:1909.11870, 2019.

[10] T. G. Debelee, F. Schwenker, A. Ibenthal, and D. Yohannes, “Survey of deep learning in breast cancer image analysis,” Evolving Systems, vol. 11, no. 1, pp. 143–163, 2020.

[11] T. G. Debelee, A. Gebreselasie, F. Schwenker, M. Amirian, and D. Yohannes, “Classification of mammograms using texture and cnn based extracted features,” in Journal of Biomimetics, Biomaterials and Biomedical Engineering, vol. 42. Trans Tech Publ, 2019, pp. 79–97.

[12] 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, 2019.

[13] Mohapatra, Sudhir Kumar. "Automatic Lung Tuberculosis Detection Model Using Thorax Radiography Image." Deep Learning Applications in Medical Imaging. IGI Global, 2021. 223-242.

[14] Debata, Biswaranjan, Sudhira Kumar Mohapatra, and Rojalina Priyadarshini. "A Systematic Literature Review on Pulmonary Disease Detection Using Machine Learning." Proceedings of the International Conference on Cognitive and Intelligent Computing: ICCIC 2021, Volume 2. Singapore: Springer Nature Singapore, 2023.

[15] Mohapatra, Sudhir Kumar, Beakal Gizachew Assefa, and Getamesay Belayneh. "A SVM Based Model for COVID Detection Using CXR Image." Advances of Science and Technology: 9th EAI International Conference, ICAST 2021, Hybrid Event, Bahir Dar, Ethiopia, August 27–29, 2021, Proceedings, Part I. Springer International Publishing, 2022.

[16] Mekonnen, A. A., Seid, H. W., Mohapatra, S. K., & Prasad, S. (2021). Developing Brain Tumor Detection Model Using Deep Feature Extraction via Transfer Learning. In Handbook of Research on Automated Feature Engineering and Advanced Applications in Data Science (pp. 119-137). IGI Global.

[17] Mohapatra, Sudhir Kumar, Srinivas Prasad, and Sarat Chandra Nayak. "Wheat Rust Disease Detection Using Deep Learning." Data Science and Data Analytics: Opportunities and Challenges (2021): 191

[18] Sinshaw, Natnael Tilahun, Beakal Gizachew Assefa, and Sudhir Kumar Mohapatra. "Transfer Learning and Data Augmentation Based CNN Model for Potato Late Blight Disease Detection." 2021 International Conference on Information and Communication Technology for Development for Africa (ICT4DA). IEEE, 2021.

[19] W. E. Fathy and A. S. Ghoneim, “A deep learning approach for breast cancer mass detection,” Int. J. Adv. Comput. Sci. Appl, vol. 10, no. 1, pp. 175–182, 2019.

[20] G. Liang, X. Wang, Y. Zhang, X. Xing, H. Blanton, T. Salem, and N.Jacobs, “Joint 2d-3d breast cancer classification,” 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 692–696, 2019.

[21] P. Gorgel, A. Sertbas, and O. N. Uc¸an, “Computer-aided classification of breast masses in mammogram images based on spherical wavelet transform and support vector machines,” Expert Systems, vol. 32, no. 1, pp. 155–164, 2015.

[22] A. Alarabeyyat, M. Alhanahnah et al., “Breast cancer detection using knearest neighbor machine learning algorithm,” in 2016 9th International Conference on Developments in eSystems Engineering (DeSE). IEEE, 2016, pp. 35–39.

[23] D. Bazazeh and R. Shubair, “Comparative study of machine learning algorithms for breast cancer detection and diagnosis,” in 2016 5th international conference on electronic devices, systems and applications (ICEDSA). IEEE, 2016, pp. 1–4.

[24] E. W. Weisstein, “Convolution,” mathworld.wolfram.com, 2020. [Online]. Available: https://mathworld.wolfram.com/Convolution.html. Acessed on: April 30, 2020.

[25] A. Zhang, Z. C. Lipton, M. Li, and A. J. Smola, “Dive into deep learning,” arXiv preprint arXiv:2106.11342, 2021.

[26] Y. K. Afework and T. G. Debelee, “Detection of bacterial wilt on enset crop using deep learning approach,” International Journal of Engineering Research in Africa, vol. 51, pp. 131–146, 12 2020.

[27] M. Talo, U. B. Baloglu, O. Yıldırım, and U. R. Acharya, “Application of deep transfer learning for automated brain abnormality classification using MR images,” Cognitive Systems Research, vol. 54, pp. 176–188, 2019.

[28] O. Yildirim, M. Talo, B. Ay, U. B. Baloglu, G. Aydin, and U. R. Acharya, “Automated detection of diabetic subject using pre-trained 2dcnn models with frequency spectrum images extracted from heart rate signals,” Computers in biology and medicine, vol. 113, p. 103387, 2019.

[29] M. Geng, Y. Wang, T. Xiang, and Y. Tian, “Deep transfer learning for person re-identification,” arXiv preprint arXiv:1611.05244, 2016.

[30] R. Mehra, “Breast cancer histology images classification: Training from scratch or transfer learning?” ICT Express, vol. 4, no. 4, pp. 247–254, 2018

[31] J. Brownlee, Machine learning mastery with Python: understand your data, create accurate models, and work projects end-to-end. Machine Learning Mastery, 2016.

[32] A. C. Wilson, R. Roelofs, M. Stern, N. Srebro, and B. Recht, “The marginal value of adaptive gradient methods in machine learning,” Advances in neural information processing systems, vol. 30, 2017.

[33] N. Ketkar and E. Santana, Deep learning with Python. Springer, 2017, vol.1.

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