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The Advantages of Employing Transfer Learning in the Classification of Breast Cancer Histopathological Images

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Abstract: Digital pathology represents a significant advancement in contemporary medicine, offering enhanced diagnostic capabilities and improved patient outcomes. Pathological examinations, which need particular steps in the diagnostic process, are standard in medical protocols and the law. Today, a new challenge is to use cutting-edge algorithms, like Convolutional Neural Networks (CNN), to classify histological images into different groups. So, the Invasive Ductal Carcinoma (IDC) dataset was used to use some well-known CNNs, such as VGG16, DenseNet169, and EfficientNetV2B3 pre-trained networks, as well as two new custom-built CNNs with four (CNN1) and five (CNN2) layers. The results show that for a 70% training to 30% testing ratio, CNN1 (0.895), CNN2 (0.882), VGG16 (0.983), DenseNet169 (0.971), and EfficientNetV2B3 (0.979) all got the best results on the test set. The results obtained with pre-trained CNNs are superior to proposed custom-built CNNs. This outcome denotes the main advantage of leveraging pre-trained CNNs in classifying breast cancer histopathological images.

Keywords: Convolutional neural networks, VGG16, DenseNet169, EfficientNetV2B3

Introduction

According to Siegel et al. (2017) and the cancer statistics report in the United States in 2022 (Siegel et al., 2022), breast cancer (BC) is one of the leading causes of cancer-related deaths among women of all ages. Conventional techniques for categorizing breast cancer molecular subtypes predominantly depend on histopathology analysis, which can be laborious, subjective, and occasionally incorrect in interpretation. The accuracy of this method in diagnosing pathologies and characterizing tissues is well known. Furthermore, such technologies, although promising, are costly and may not be easily accessible in multiple nations and healthcare systems (Rashmi et al., 2021)

Deep learning (DL) has recently become a revolutionary tool in various domains, particularly in medical image processing. Deep learning, a subset of machine learning, employs multilayered neural networks to discern complex patterns in unprocessed data without the necessity for manual feature extraction, representing a significant advancement over conventional techniques (Szilágyi & Kovács, 2024; Ragab et al., 2022). Convolutional Neural Networks are enabled to differentiate the malignant versus non-malignant (benign) tissue,

which exhibits alterations in the normal pattern of breast parenchyma that are not directly associated with the progression to malignancy.

Many researchers have been motivated to use deep learning techniques for histopathology image classification as a result of the recent significant advancements and outstanding results in the fields of computer vision (CV) and image processing (IP). Convolutional neural networks (CNNs) are the dominant type of deep learning architecture, excelling in both the classification of images and feature extraction (Litjens et al., 2017). Pre-trained CNN models are neural networks that have undergone training on extensive datasets, usually for general image recognition purposes, and are accessible for external utilization.

This study examines three distinct pre-trained CNNs: VGG16, DenseNet169, and EfficientNetV2B3, for feature extraction from breast cancer histopathology images. The histopathological images of breast cancer are sourced from the publicly accessible Invasive Ductal Carcinoma (IDC) dataset. This work utilized transfer learning to construct four pre-trained models using the IDC dataset instead of employing a model with arbitrary weights from inception. The results obtained are comparable to those described in the following studies.

Simonyan et al. (2023) focused on the accurate classification of breast cancer using deep learning models for medical image processing, employing four pre-trained models: DenseNet201, ResNet50, ResNet101, and MobileNet-v2. Kumar and Murali (2024) discussed the importance of early breast cancer detection and the use of EfficientNetB6, ResNet34, VGG-19, MobileNetV2, and ResNet50 for the classification of medical histopathological images.

An approach for classifying the same BC histopathology images using pre-trained CNNs by Abdulaal et al. (2024) was proposed. This study included Inception V3 Net, VGG19, Alex Net, ResNet-18, Google Net, Shefflenet, Mobile Net, ResNet 101, Inception ResNetV2 Net, and Squeeze Net. Sumitha and Isaac (2024) proposed one pre-trained CNN model (ResNet152v2) for the automated classification of benign and malignant BC using histopathological images. Only one pre-trained CNN was proposed by Mani et al. (2023) The suggested model (VGG-16) classifies breast histopathology images as benign or cancerous, yielding superior results.

Recently, an interesting result was presented by Korkmaz and Kaplan (2025). This study includes three pre-trained models: VGG16, MobileNet, DenseNet201, and a custom-built CNN. The higher accuracy rate was obtained using the custom-built CNN model (Korkmaz & Kaplan, 2025).

Materials and Methods

Image Dataset

A 40x scan of 162 whole-mount slide images of BC specimens made up the original dataset. A total of 277,524 patches measuring 50 x 50 were retrieved, comprising 198,738 non-IDC and 78,786 IDC samples. The images have a PNG extension and are labeled with “0” for non-IDC and “1” for IDC samples. The dataset is stored at the web address, and the data of the last access is 19 February 2025 (https://www.kaggle.com) (Janowczyk& Madabhushi, 2016). In this study, the dataset was split into 70% for training and 30% for testing. The same samples are shown in Figure 1.

(a1) (a2) (a3)

(b1) (b2) (b3)

Figure 1. The examples of IDC (a1, a2, a3) and non-IDC b1, b2, b3)

Hardware and Software

All experiments were run on a PC with the architecture Apple Mac Studio (2022), Apple M1 Max, 32GB, 1TB SSD, and 32-core GPU. The programming environment was Python (3.12.9), with the following main libraries: (i) TensorFlow (2.18.0), (ii) Keras (3.6.0), and (iii) Visualkeras (0.1.4.3).

Pre-trained CNN

Transfer learning approaches are utilized to retrain CNNs already trained in a given domain, enabling their application to various datasets. The primary advantage is the conservation of resources, as the model is partially reutilized, with scenarios varying from retraining the network entirely to retraining only selected components, generally associated with categorization (Tsalera et al., 2021).

VGG-16 is a CNN of 16 layers. A trained version of the network trained on over a million images is available for loading from the ImageNet database. The pre-trained network is capable of classifying images into 1000 object classes (Abdulaal et al., 2024; Kumar & Murali, 2024; Mani et al., 2023). Convolutional neural networks yield effective outcomes in image processing, particularly in object detection and classification applications. This effort aims to train a convolutional neural network for classifying photos from the CIFAR-10 database using Keras.

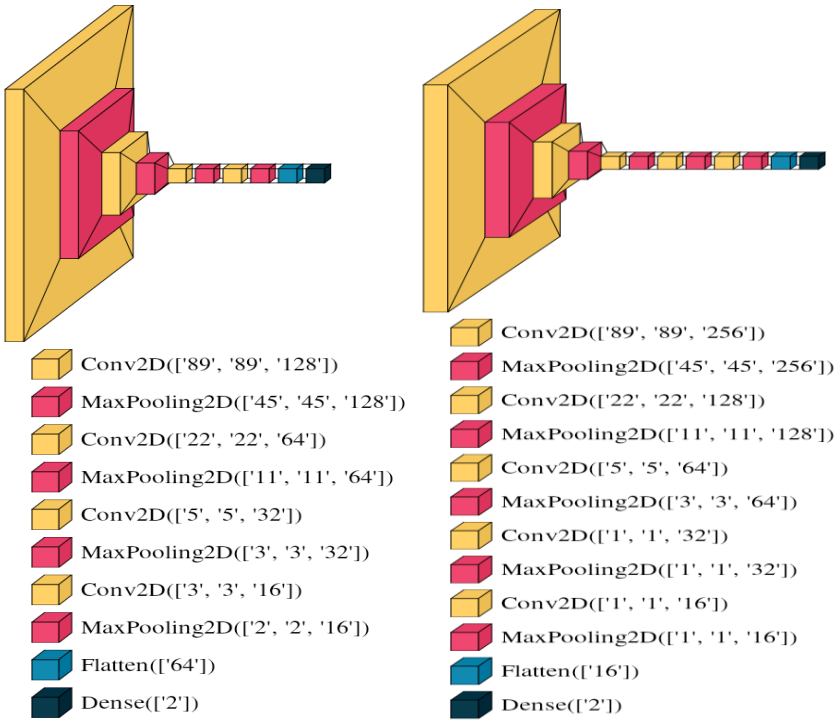
The DenseNet-169 CNN is pre-trained on ImageNet and CIFAR-10 using the Keras tool. Her architecture consists of convolutional layers succeeded by subsampling layers (average This CNN facilitates the identification of features and edges inside the image (Mani et al., 2023). The EfficientNetV2B3 belongs of EfficientNet CNN family intoruced by Tan and Le (2021). EfficientNet's fundamental concept is a novel scaling approach that consistently adjusts all dimensions of depth, width, and resolution using a compound coefficient.

Custom-built CNN

Besides pre-trained CNNs, this paper presents a customized, optimal, and efficient model to illustrate the application of a CNN-based technique for IDC classification in histopathological images. The proposed architectures utilized a 4-convolutional-layer (CNN1) model, Figure 2.(a), and a 5-convolutional-layer (CNN2) model, Figure 2.(b), respectively. Their implementation keeps on the following steps:

i Access publicly available Invasive Ductal Carcinoma (IDC) dataset;
ii Load images onto Python environment.
iii Configure hyperparameters and pre-processing options for image data augmentation.
iv The previous images are the inputs of the custom-built CNN model.
v Dropout layer is added to prevent the overfitting process.
vi The convolutional layers give the depth of CNN.
vii MaxPooling layers are proposed to reduce the spatial dimensions of the input volume data.

viii Output size is depicted by the FC layer, and the SoftMax function is applied to obtain a binary classification.



(a) (b)

Figure 2. Custom-built CNNs: (a) four layers (CNN1); (b) five layers (CNN2).

The hyperparameters used for all CNNs were the size of images 180x180, the batch size of 16, the canal number of 3 and 20 epochs.

Performance Evaluation

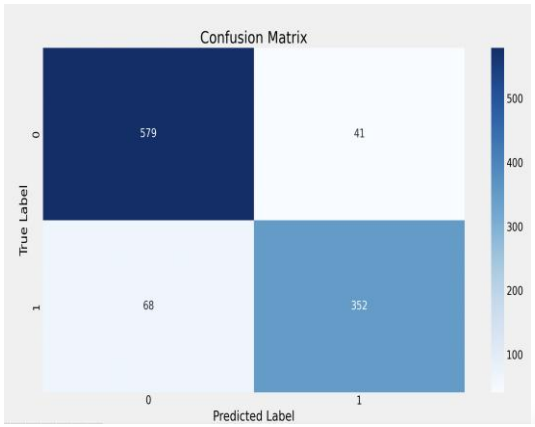
The objective of this study was to assess efficacy custom-built and pre-trained CNNs. The confusion matrix having the form $\begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$ (TN-true positive, FP-false positive, FN-false negative and TN true negative) is used in this sense. The relevat metric what reflect the prediction of model is accuracy, it has the equation $Accuracy = (TP + TN)/(TP + TN + FP + FN)$ (Tăbăcaru et al., 2024).

Results and Discussions

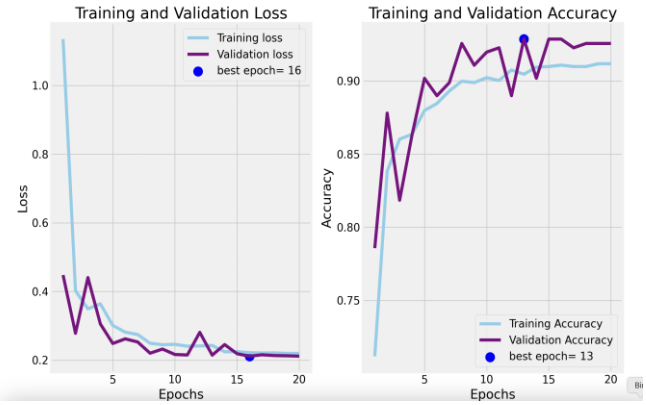
In this section, we assessed the efficacy of suggested deep learning models by analyzing the predicted accuracy. Initially, we emphasized the performance indicated by pre-trained CNNs and then for custom-built CNNs, followed by a discussion on the competitiveness of our suggested models to recently published studies, particularly with the classification of BC histopathology images.

The VGG16, DenseNet169, and EfficientNetV2B3 (Moldovanu et al., 2024; Tabacaru et al., 2023) models yielded excellent outcomes when analyzing the histopathological images for the classification of IDC. The confusion matrix obtained for the test stage for each CNN is shown in Figure 3, first column. The accuracy and loss function for training validation stages for each epoch are shown in Figure 3; also, the best epoch, when the accuracy is maximum, is marked in the second column.

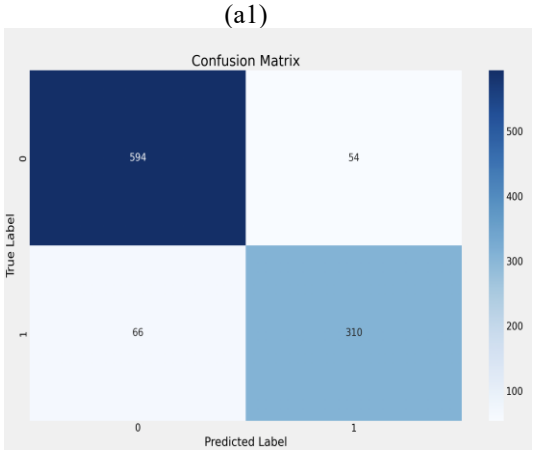
As shown in the first column, several histopathological BC images were incorrectly classified. The DNN1 and DNN2 had a low performance; these misclassified more samples in comparison with pre-trained. Table 1 shows all the information provided by the runs performed. In addition to the accuracy and loss metrics computed for the test stage, the complementary details of the same metrics are provided for the training and testing stages.



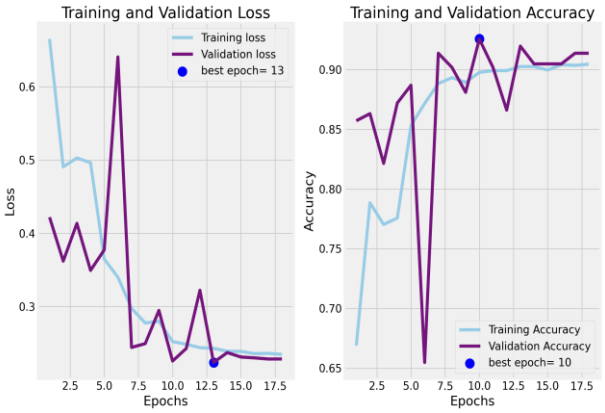
(a1)



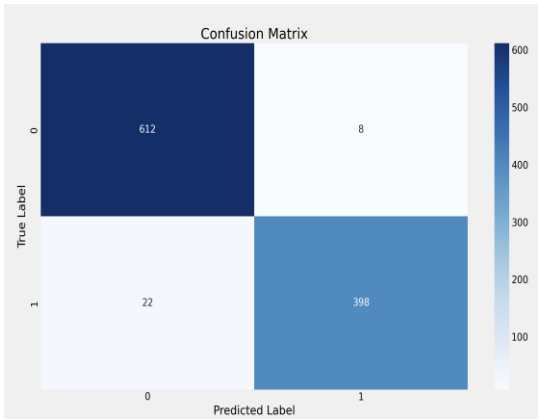
(a2)



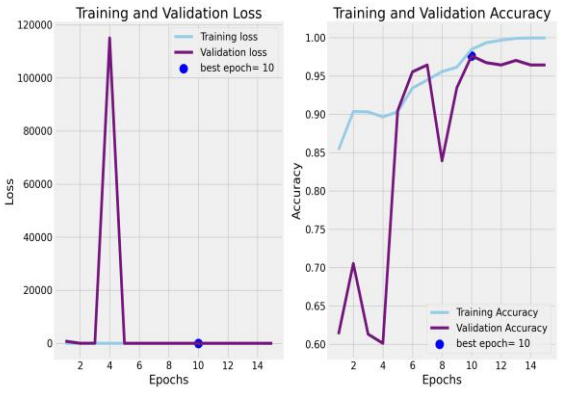
(b1)



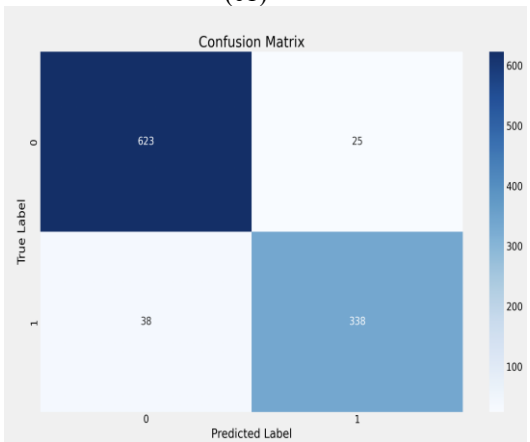
(b2)



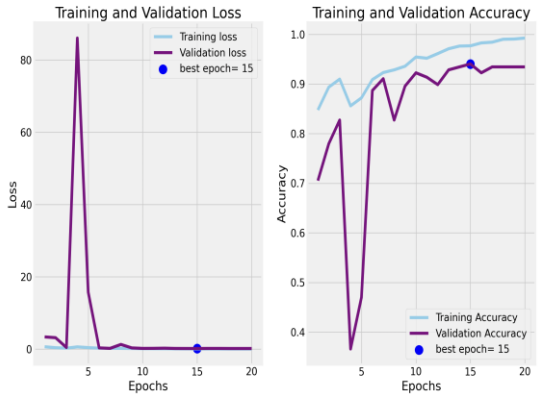
(c1)



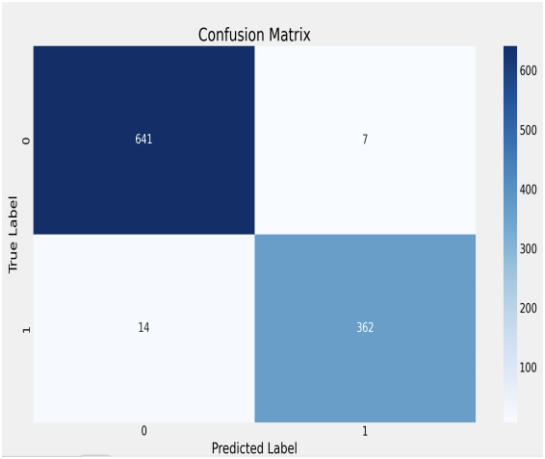
(c2)



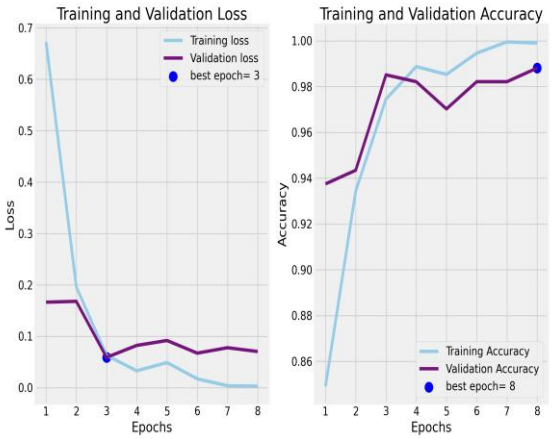
(d1)



(d2)



(e1)



(e2)

Figure 3. (a) DNN1; (b) DNN2; (c) DenseNet169; (d) VGG16; (e) EfficientNetV2B3

Table 1. The metrics computed for each CNN and run stage

CNN	Metrics	Training	Validation	Testing
VGG16	Loss	0.120	0.169	0.166
	Accuracy	0.957	0.940	0.938
DenseNet169	Loss	0.055	0.063	0.071
	Accuracy	0.980	0.976	0.971
EfficientNetV2B3	Loss	0.012	0.059	0.068
	Accuracy	0.995	0.985	**0.979**
CNN1	Loss	0.22	0.211	0.236
	Accuracy	0.908	0.928	0.895
CNN2	Loss	0.238	0.223	0.269
	Accuracy	0.904	0.919	0.882

Table 2 Comparing with state-of-the-art-methods

References/year	Pre-trained CNNs	The best accuracy
(Simonyan et al., 2023)	DenseNet201, ResNet50, ResNet101 MobileNet-v2	DensNet201(91.37%)
(Kumar and Murali, 2024)	EfficientNetB6, ResNet34, VGG-19, MobileNetV2, ResNet50	MobileNetV2 (99%) ResNet50 (99%)
(Abdulaal et al., 2024)	Inception V3 Net, VGG19, AlexNet, ResNet-18, Google net, Shefflenet, Mobile net, Resnet 101, Inception ResnetV2 Net, Squeeze net	Inception-V3Net (99.1%)
(Sumitha and Isaac, 2024)	ResNet152v2	ResNet152v2 (96.47%)
(Mani et al., 2023)	VGG-16	VGG-16 (96.9%.)
(Korkmaz and Kaplan, 2025)	VGG16, MobileNet, DenseNet201 A custom-built CNN	Custom-built CNN (93.80%)
The proposed method	EfficientNetV2B3	97.9%

The efficacy of our suggested method can be evaluated against several cutting-edge studies utilized for the classification of BC histopathology images. Many of these innovative deep learning methodologies are based on pre-trained CNNs (Ashraf et al.,2024; Abdulhussain et al., 2022; Kucharski et al., 2020); the exception is the paper (Davri et al.,2022), which, besides pre-trained CNNs, uses a custom-built. Table 2 shows the recent state-of-the-art method, as well as the proposed method. The best value obtained by a CNN among those proposed in terms of accuracy is mentioned in the last column.

In summary, the findings indicated that our proposed deep learning model is capable of extracting features from histopathological images of BC and using the Softmax function to classify them. The comparison method revealed that the outcomes of our suggested pre-trained CNNs are competitive with several state-of-the-art research studies utilizing comparably larger datasets.

Conclusion

This research utilizes two custom-built CNN models for extracting features and classification tasks on BC histopathological images. The publicly available dataset was archived by several institutions. The BC histopathological images dataset consists of two categories, namely, non-IDC and IDC samples. The custom-built CNN1 with four layers observed in this research achieved in the test stage an accuracy of 89.5%. Also, this research investigated the classification of BC histopathological images using pre-trained CNN models. The performance of three pre-trained models, including VGG16, DenseNet169, and EfficientNetV2B3, was evaluated using the same dataset. The EfficientNetV2B3 outperformed the best accuracies of 97.9 in the testing stage. Future directions of this research entail the augmentation of our dataset and the incorporation of images for multi-class classification challenges. Additionally, the integration of other pre-trained models is necessary in subsequent work. At some point, it would be intriguing to apply analogous CNNs to histopathology images of various cancers, including lung and colon cancer.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

Conflict of Interest

The authors declare that they have no conflicts of interest

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References

Abdulaal, A.H., Valizadeh, M., Amirani, M.C., & Shah, A.S. (2024). A self-learning deep neural network for classification of breast histopathological images, *Biomed. Signal Process. Control*, *87*, 105418.

Janowczyk, A., Madabhushi, A. (2016) Deep learning for digital pathology image analysis: a comprehensive tutorial with selected use cases. *Journal of Pathology Informations, 7,* 29.

Ashraf, A., Nawi, N.M., Shahzad, T., Aamir, M., Khan, M.A., & Ouahada, K. (2024). Dimension reduction using dual-featured auto-encoder for the histological classification of human lungs tissues. *IEEE Access*, *12,* 104165–104176.

Abdulhussain, F.A., Adnan, M., Radhi, HAl-Mualm, M., Hasen -Alubaidy, M., Salih, M., & Saadoon S.J. (2022). Automatic diagnosis of breast cancer in histopathologic images based on convolutional autoencoders and reinforced feature selection. *Majlesi Journal of Electrical Engineering*,*16*(4), 89-95.

Davri, A., Birbas, E., Kanavos, T., Ntritsos, G., Giannakeas, N., Tzallas, A.T., & Batistatou, A. (2022). Deep learning on histopathological images for colorectal cancer diagnosis: A systematic review. *Diagnostics*, *12,* 837.

Korkmaz, M., & Kaplan, K. (2025). Effectiveness analysis of deep learning methods for breast cancer diagnosis based on histopathology images, *Applical Sciences, 15*(3), 1005.

Kucharski, D., Kleczek, P., Jaworek-Korjakowska, J., Dyduch, G., & Gorgon, M. (2020). Semi-supervised nests of melanocytes segmentation method using convolutional autoencoders. *Sensors*, 20, 1546.

Kumar, V., & Murali G., (2024). Optimized deep learning approaches for lung and colon cancer classification using histopathological images. *Proceedings from 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS),* 1665-1669.

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, 60-88.

Mani, C., Kamalakannan, R. K., Pandu Rangaiah, J., & Anand Y. (2023). Bio-inspired method for breast histopathology image classification using transfer learning. *Journal of Artificial Intelligence and Technology*, *4*(2), 89-101

Moldovanu, S., Tăbăcaru, G., & Barbu, M. (2024). Convolutional neural network–machine learning model: hybrid model for meningioma tumour and healthy brain classification. *Journal of Imaging*,*10*(9), 235.

Ragab, M., Albukhari, A., Alyami, J., & Mansour R.F. (2022). Ensemble deep-learning-enabled clinical decision support system for breast cancer diagnosis and classification on ultrasound images. *Biology*, *11*(3), 439.

Rashmi, R., Prasad, K., & Udupa, C. B. K. (2022). Breast histopathological image analysis using image processing techniques for diagnostic purposes: A methodological review. *Journal of Medical Systems*, *46*(1), 7.

Siegel, R.L., Kimberly M. D., Hannah, F. E., & Ahmedin, J. (2022). Cancer statistics. *CA: Cancer Journal for Clinicians*, *72* (1), 7-33.

Siegel, R.L., Miller K.D., Jemal A. (2017). Cancer statistic. *CA: Cancer Journal for Clinicians*,*67*(1), 7-30.

Simonyan, E.O., Badejo, J.A., & Weijin, J.S. (2023). Histopathological breast cancer classification using CNN, *Materials Today*: *Proceedings,105*, 268-275.

Sumitha, R. S., Isaac, R. (2024). Transfer learning-based CNN model for the classification of breast cancer from histopathological images. *International Journal of Advanced Computer Science & Applications*,*15*(4), 270.

Szilágyi, L., & Kovács, L. (2024). Artificial ıntelligence technology in medical ımage analysis. *Applied Sciences*, *14*(5), 2180.

Tăbăcaru, G., Moldovanu, S., Răducan, E., & Barbu, M. (2023). A robust machine learning model for diabetic retinopathy classification. *Journal of Imaging*, *10*(1), 8.

Tan, M., & Le, Q. (2019, May). Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning* (pp. 6105-6114). PMLR.

Tsalera, E., Papadakis, A., & Samarakou, M. (2021). Comparison of pre-trained CNNs for audio classification using transfer learning. *Journal of Sensor and Actuator Networks*, *10*(4), 72

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