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Classification of breast cancer using a precise deep learning model architecture

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ABSTRACT

Breast cancer is an important topic in medical image analysis because it is a high-risk disease and the leading cause of death in women. Early detection of breast cancer improves treatment outcomes, which can be achieved by identifying it using mammography images. Computer-aided diagnostic systems detect and classify medical images of breast lesions, allowing radiologists to make accurate diagnoses. Deep learning algorithms improved the performance of these diagnoses systems. We utilized efficient deep learning approaches to propose a system that can detect breast cancer in mammograms. The proposed approach adopted relies on two main elements: improving image contrast to enhance marginal information and extracting discriminatory features sufficient to improve overall classification quality, these improvements achieved based on a new model from scratch to focus on enhancing the accuracy and reliability of breast cancer detection. The model trained on the digital database for screening mammography (DDSM) dataset and compared with different convolutional neural network (CNN) models, namely EfficientNetB1, EfficientNetB5, ResNet-50, and ResNet-101. Moreover, to enhance the feature selection process, we have integrated adam optimizer in our methodology. In evaluation, the proposed method achieved 96.5% accuracy across the dataset. These results show the effectiveness of this method in identifying breast cancer through images.

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1. INTRODUCTION

Cancer is a complex disease, which can be explained as the gradual increase and spread of abnormal cells within the body [1]. Breast cancer is one of the most prevalent cancers, posing an important global health challenge, as it is a major cause of death among women worldwide. Mortality rates from it exceeded diseases such as malaria or tuberculosis. The World Health Organization (WHO) also reported in 2018 that there are more than 17 million cancer cases worldwide, and stated that this number is expected to increase significantly in the coming years [2]. There are tremendous efforts invested in intensive research by medical experts and scientists to find the best treatment for breast cancer and its prevention, but the changing nature of the disease is one of the most prominent challenges that scientists face to treat it. The disease begins in some female breast tissue and then tries to move to vital organs. It is therefore important to observe the excessive growth of mammalian cells which can lead to the formation of tumors in females. These tumors are divided, crucially, into two categories: cancerous and non-cancerous, and their differentiation is assessed by BI-RADS scores [3].

Benign tumors are classified as non-cancerous and often treatable, and they do not pose a direct threat to women's lives, but malignant tumors, on the contrary, can spread to other areas and tissues through the lymphatic system or bloodstream, necessitating treatment with surgery or radiation therapy to combat this malignant disease. Mammography, which involves applying a light dose of X-ray to the breast, is the primary way to detect the disease. Despite this, researchers have explored several biomedical imaging techniques to support specialist radiologists in their mission to detect and treat the disease. The computer aided diagnosis (CAD) model is considered the most prominent assistant to radiologists in the field of identifying malignant breast cancer tumors [4]. This is due to its ability to recognize images and the possibility of classifying them, so it is the preferred choice for this vital field. Deep learning techniques have been employed in this field for their ability to extract deep features to diagnose disease directly from the source of mammography, so it is the most effective and reliable approach in the medical field [5], [6].

Accurate diagnosis of breast abnormalities is a formidable challenge for diagnosing breast cancer [7], and traditional methods remain low-level in detecting the diverse spectrum of breast lesions [8], [9]. Therefore, employing deep learning for the purpose of diagnosis significantly improves performance and provides a glimmer of hope for controlling this disease through early detection [10]. Identifying the correct traits as well as their appropriate distribution is a key aspect of accurate classification, especially when it comes to distinguishing between benign and malignant breast lesions. Therefore, the use of deep learning helps to build a reliable inspection system that can be added within CAD devices [11]. The proposed oncology diagnostic system is capable of identifying cancer in its initial stages, as well as effectively managing the disease in all subsequent stages.

The rest of the paper is structured as follows: Section 2 reviews different related work, while section 3 dataset and preparation. Section 4 describes methodology. Section 5 the experimental work and discusses the results achieved, while section 6 presents the conclusions.

2. RELATED WORKS

In recent years, deep learning algorithms have made a significant development in various fields, and have been used in the detection of breast cancer through mammography images, as they have alleviated the complex challenges associated with distinguishing between benign and malignant lesions as well as increasing the accuracy and effectiveness of the early diagnosis process. Chougrad *et al.* [12] The study presented the pioneering DFeBCD technique in identifying and detecting breast cancer by classifying mammograms using a combination of SVM and ELiEC classifier, achieving an accuracy level of 80.30%. The convolutional neural network (CNN) was also used in [13] to determine the possible locations of the tumor in the image by revealing the possibility of pixels being associated with breast deformities, which is an effective step in localizing the lesion, and the study achieved a prediction accuracy of 93.33%, which is high accuracy so it is a big step to detect and classify breast abnormalities.

Dhungel *et al.* [14] an innovative deep learning CAD technique consisting of four sequential phases was introduced, initially integrating generalized morphological component analysis (GMC) and deep belief network (DBN) to extract potential lesions. Then, it integrates area-based convolutional neural networks (R-CNN) and conditional random fields (CRF) to effectively reduce the error rate. The results of the work show that deep learning has improved disease detection systems, increasing the chances of a more accurate diagnosis of breast cancer. Harefa *et al.* [15], a new model was presented based on the use of the gray level coincidence matrix (GLCM), and the use of support vector machine (SVM) technology to classify images and detect disease by training the model on the breast analysis society (MIAS) database, where the method obtained promising results with an accuracy rate of 93.88%. In the same way, [16] introduced an algorithm that effectively separates diseased tissue within a mammogram, which helps minimize the inclusion of distant pixels that do not extend a connection to the tumor. Modern classification models used the DBN in [17] to classify breast deformities, and the custom CNN was used in [18] For the same purpose, the classification categories were divided into benign and malignant categories. Rajinikanth *et al.* [19] the neural network was trained to classify thermal images of the breast to detect the disease and the study achieved an accuracy of 92%. These studies did not achieve the accuracy we were hoping for, so we built our own model to improve the accuracy of disease detection.

3. DATASET AND PREPARATION

The proposed system was evaluated using the widely recognized digital database of mammography screening (DDSM) [20]. The DDSM dataset is a comprehensive collection that includes compressed breast radiography films scanned and stored in Stretch (JPEG). It consists of 2620 breast photo samples and is divided into 43 volumes. It is worth noting that each breast case has two modes of display that were accurately captured from the median lateral oblique (MLO) and cranio-caudal (CC), forming images with immense information [21]. One of the most notable features of the DDSM dataset is that it contains images of various cases associated with benign and malignant breast cancer. In addition to containing vital information related to the exact location of lesions, which greatly facilitates the process of detecting breast diseases, making it the most used in the field of research to detect and diagnose breast cancer, as clearly shown in Figure 1.

All images in the DDSM database undergo a pre-processing process, which has a major role in clearing images of unwanted noise, in addition to raising the quality of images using image enhancement techniques by applying multi-threshold terminal equation as shown in Figure 2. This figure shows the breast image before the pre-processing stage as shown in Figure 2(a), while the image after this stage is shown in Figure 2(b). The pre-processing stage helps in obtaining clear images and ensuring that the parameters of the image are not lost. Followed by a key step of balancing the training dataset, this delicate balance is central to ensuring continuous updates of parameters and achieving strong performance for deep learning models in all categories [22], [23].

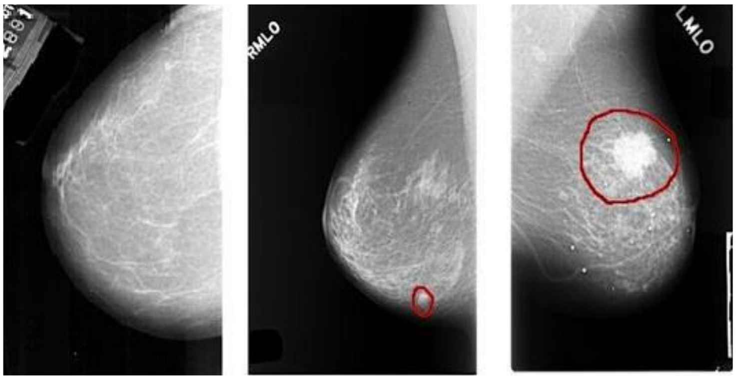
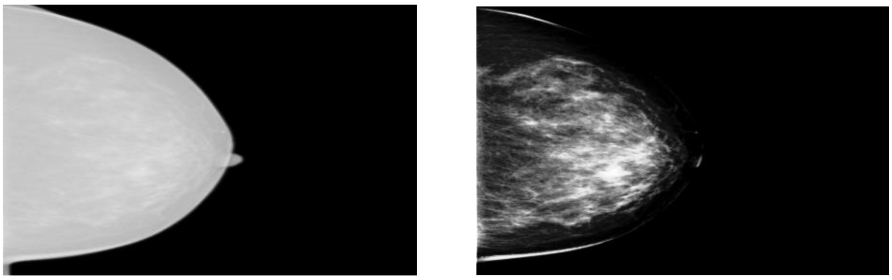


Figure 1. Examples of normal, benign, and malignant Mammogram images from DDSM dataset



(a) (b)

Figure 2. The outcomes of the image pre-processing, noise remove and image enhancement, (a) the input image and (b) the prepocessed image

4. METHOD

It is known that the process of training the deep convolutional neural network (DCNN) model is a large time, often extending for days or even weeks in addition to costly material resources, and to overcome this challenge, the concept of transfer learning emerges as a valuable approach to significantly accelerate the training process. This approach uses the weight parameters of pre-trained CNN models obtained from large-scale databases such as ImageNet [24], to avoid the need to start training from scratch. The process of transferring learning to fine-tuning the parameters of the pre-trained network in order to adapt it to the nuances of the new classification problem, after the initial training phase, requires adjustment. This is where the architectural hierarchy of the neural network emerges where the lower layers capture the patterns specific to the task, while the upper layers capture broader and more general features. Meanwhile, the upper layers of the pre-trained model are frozen. In this way, it is possible to benefit from the structure of the layers in the pre-trained model as well as the possibility of adapting the lower layers of the model to train on new data. Although, the pre-trained models carry the biases and assumptions from their original training data, which have a negative affect on the model performance.

In this work, a typical model from scratch was created for the purpose of classifying breast tumors into three categories. The proposed model has been customized CNN layers and optimized to get a high-performance classification result. For the purpose of evaluating the proposed model, the data were trained on the following pre-trained algorithms: EfficientNetB1, EfficientNetB5, ResNet-50 and ResNet-101. As these models are among the most important methods that have been used to extract complex patterns from images, especially medical ones, also, they focus in their work on image accuracy, layer depth and channel width, which leads to increase information processing and thus capturing complex patterns and features from the given data. The architecture of the EfficientNet network follows a wonderful strategy that enables the model to upgrade the resolution of the image, which increases the opportunity to capture difficult and complex details in the image, this architecture enables the neural network to handle sensitive data, as its innovative design achieves a great balance from all aspects as shown in Figure 3 of the EfficientNetB1 model that has been utilized in this work [25], [26]. The ResNet model, the residual neural network, is designed with high precision that enables us to train deep neural networks exceptionally. This innovation lies in the concept of "skipping connections", which is the centrepiece of its remarkable success and that distinguishes it from traditional neural network structures. It is strategically designed to enable the smooth flow of information across layers, such as a well-connected neural method, and the ResNet model effectively addresses the problem of vanishing gradients [27]. This simplifies the training process, since the network can focus on improving the residues, ensuring that even in the deepest structures, accuracy is not compromised [28], [29]. One of the notable features of ResNet is its versatility. They are available at different depths, indicated by designations such as ResNet-18 and ResNet-50, as shown in Figure 4. These designations indicate the number of layers in the structure, allowing practitioners to select a configuration corresponding to their specific task and computational resources. Whether it's image classification, object detection, or image segmentation, ResNet has consistently proven to be proficient in a myriad of computer vision tasks.

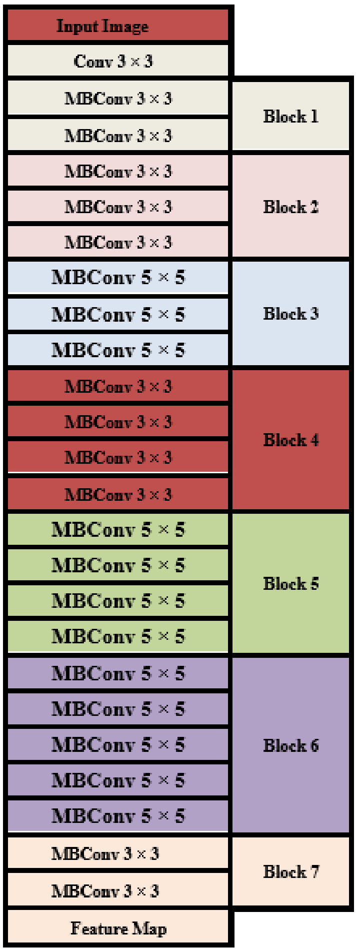


Figure 3. The basic building block of EfficientNetB1 [26]

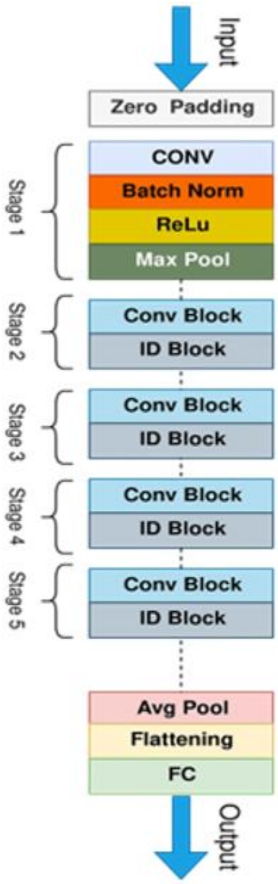


Figure 4. The basic building blocks of ResNet-50

In the proposed method, we have customized the CNN layers and employed the Global Average Pooling in the Max Pooling layer to reduce model workload by averaging values instead of selecting the maximum values in the pooling layer. Moreover, to prevent overfitting the function of callbacks (Early_Stopping and Model_Check_point) and a dropout layer are used. Callbacks help in resolving errors and enhancing model accuracy by intervening during training. The dropout layer enhances independence among neurons by randomly deactivating some of them during each iteration. While, the Model_Check_point saves the best model parameters based on monitoring the validation accuracy. To control the learning rate reduction the function of (Reduce_LROn_Plateau) has been utilized with a factor of 0.31 and endurance of 2. The Dense layer categorized images into one of three classes using the SoftMax function for multi-class classification." Categorical Cross entropy" served as the loss function due to the multi-class output. The model employed the Adam optimizer with accuracy and loss as metrics. For validation, a 20% data split was used. Epochs and batch size were optimized using Gaussian process, mapping hyperparameters to outcomes. The argmax function determined the most likely label by selecting the maximum value from each prediction row. This value index represented the outcome. The CNN architecture is depicted in Figure 5.

Input Layer	299 × 299 × 3
Conv2D	3 × 3 × 3 × 64
BatchNormalization	
Conv2D	3 × 3 × 64 × 64
BatchNormalization	
MaxPooling2D	
Dropout	
Conv2D	3 × 3 × 64 × 128
BatchNormalization	
MaxPooling2D	
Dropout	
Conv2D	3 × 3 × 128 × 128
BatchNormalization	
MaxPooling2D	
Dropout	
Conv2D	3 × 3 × 128 × 128
BatchNormalization	
MaxPooling2D	
Dropout	
Flatten	
Dense	
BatchNormalization	
Dropout	
Dense	128 × 3

Figure 5. The building blocks of the proposed CNN model

5. EXPERIMENTAL WORK AND RESULTS

In this work several tools and libraries for programming deep learning algorithms and neural network modelling were used, which have a major role in the development and evaluation of our breast cancer classification models. These libraries included TensorFlow, Keras, and PyTorch. In addition, we have used Many helper libraries such as Tqdm, NumPy, Pandas, Matplotlib and sklearn, each contributing its own unique capabilities to simplify data processing, visualization, and performance evaluation. The study aims to enhance classification accuracy, reduce training time for the deep learning model. Our efforts are briefly summarized in Table 1, where the performance of carefully selected pre-trained architectures is documented. Notably, each of the pre-trained networks showed remarkable classification accuracy, demonstrating its strength in the task of detecting breast cancer, with scores ranging from 90.1% to 94.3%. A notable achievement worth highlighting is the performance of our proposed model, which showed promising results across multiple metrics, including accuracy, and area under curve (AUC).

The EfficientNetB5 model was employed as an efficient model, having the highest accuracy when applied to a DDSM dataset. On the other hand, the training of the EfficientNetB1 and ResNet-50 models resulted in slightly lower performance. The depth and complexity of the model is proof of its accuracy. However, it is necessary to strike a balance between performance and resource utilization. The CNN model developed on pre-trained models, the results of which are clearly shown in Figure 6. This profound improvement in accuracy underscores the strength of the proposed model and its importance in developing deep learning models to accomplish very specific tasks such as analysing medical images.

Table 1. Comparison of model's performance

Model	Accuracy	AUC	Precision	Recall	F1-score
Proposed Model	96.5	96.3	0.95	0.95	0.96
EfficientNetB5	94.3	96.02	0.94	0.91	0.93
ResNet-101	93.5	95.3	0.94	0.92	0.92
EfficientNetB1	91.3	92.2	0.91	0.91	0.92
ResNet-50	90.12	91.3	0.9	0.91	0.91

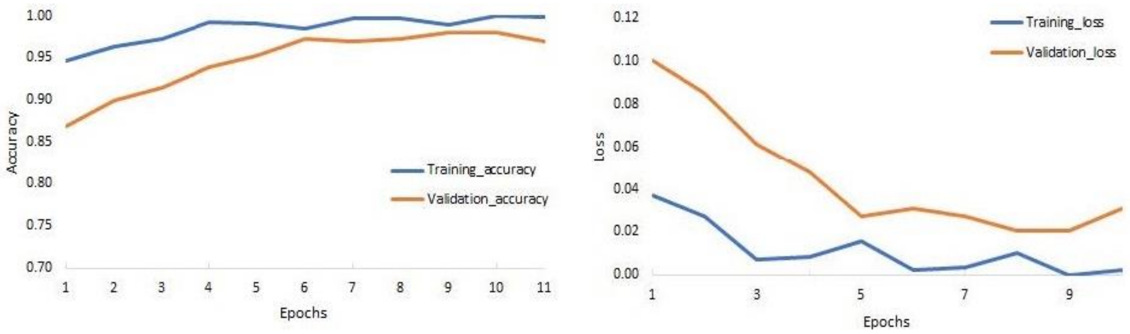


Figure 6. The accuracy graph for the proposed model

6. CONCLUSION

In this work, a CNN model was designed with its ability to classify complex cases of breast cancer, where the data was trained after finely adjusting the model and improving it to obtain the most accurate results that can be obtained from mammography images, and the proposed model was compared with previously trained models. Which contributed to the discovery of different ways to achieve the best accuracy in the results, which facilitates the process of diagnosing the disease with high accuracy and reliability, which benefits the medical staff working in the field.

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AUTHOR CONTRIBUTIONS STATEMENT

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Murtadha Al-Ghadhanfari		✓				✓		✓	✓	✓	✓	✓		
Fajer Fadhil	✓		✓	✓		✓			✓		✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee; or: The research related to animal use has been complied with all the relevant national regulations and institutional policies for the care and use of animals.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the Digital Database for Screening Mammography (DDSM) at http://doi.org/10.7937/K9/TCIA.2016.7O3ZH2DS, [20].

REFERENCES

[1] C. Xu *et al.*, "Adenosquamous carcinoma of the breast: a population-based study," *Breast Cancer,* vol. 28, pp. 848-858, 2021, doi: 10.1007/s12282-021-01222-3.

[2] S. J. S. Gardezi, A. Elazab, B. Lei, and T. Wang, "Breast cancer detection and diagnosis using mammographic data: Systematic review," *Journal of medical Internet research,* vol. 21, no. 7, p. e14464, 2019, doi: 10.2196/14464.

[3] M. A. Al-Antari, M. A. Al-Masni, M.-T. Choi, S.-M. Han, and T.-S. Kim, "A fully integrated computer-aided diagnosis system for digital X-ray mammograms via deep learning detection, segmentation, and classification," *International journal of medical informatics,* vol. 117, pp. 44-54, 2018, doi: 10.1016/j.ijmedinf.2018.06.003.

[4] Z. Assari, A. Mahloojifar, and N. Ahmadinejad, "Discrimination of benign and malignant solid breast masses using deep residual learning-based bimodal computer-aided diagnosis system," *Biomedical Signal Processing and Control,* vol. 73, p. 103453, 2022, doi: 10.1016/j.bspc.2021.103453.

[5] H. Pezeshki, M. Rastgarpour, A. Sharifi, and S. Yazdani, "Extraction of spiculated parts of mammogram tumors to improve accuracy of classification," *Multimedia Tools and Applications,* vol. 78, pp. 19979-20003, 2019, doi: 10.1007/s11042-019-7185-4.

[6] T. Kooi *et al.*, "Large scale deep learning for computer aided detection of mammographic lesions," *Medical image analysis,* vol. 35, pp. 303-312, 2017, doi: 10.1016/j.media.2016.07.007.

[7] W. Xie, Y. Li, and Y. Ma, "Breast mass classification in digital mammography based on extreme learning machine," *Neurocomputing,* vol. 173, pp. 930-941, 2016,, doi: 10.1016/j.neucom.2015.08.048.

[8] N. H. Mukand *et al.*, "The association between physical health-related quality of life, physical functioning, and risk of contralateral breast cancer among older women," *Breast Cancer,* vol. 29, no. 2, pp. 287-295, 2022, doi: 10.1007/s12282-021-01309-x.

[9] S. Maqsood and U. Javed, "Multi-modal medical image fusion based on two-scale image decomposition and sparse representation," *Biomedical Signal Processing and Control,* vol. 57, p. 101810, 2020, doi: 10.1016/j.bspc.2019.101810.

[10] R. Agarwal, O. Diaz, X. Lladó, M. H. Yap, and R. Martí, "Automatic mass detection in mammograms using deep convolutional neural networks," *Journal of Medical Imaging,* vol. 6, no. 3, pp. 031409-031409, 2019, doi: 10.1117/1.JMI.6.3.031409.

[11] N. Chouhan, A. Khan, J. Z. Shah, M. Hussnain, and M. W. Khan, "Deep convolutional neural network and emotional learning based breast cancer detection using digital mammography," *Computers in Biology and Medicine,* vol. 132, p. 104318, 2021, doi: 10.1016/j.compbiomed.2021.104318.

[12] H. Chougrad, H. Zouaki, and O. Alheyane, "Deep convolutional neural networks for breast cancer screening," *Computer methods and programs in biomedicine,* vol. 157, pp. 19-30, 2018, doi: 10.1016/j.cmpb.2018.01.011.

[13] Y. Brhane Hagos, A. Gubern Mérida, and J. Teuwen, "Improving breast cancer detection using symmetry information with deep learning," in *International Workshop on Reconstruction and Analysis of Moving Body Organs*, 2018: Springer, pp. 90-97, doi: 10.1007/978-3-030-00946-5_10.

[14] N. Dhungel, G. Carneiro, and A. P. Bradley, "A deep learning approach for the analysis of masses in mammograms with minimal user intervention," *Medical image analysis,* vol. 37, pp. 114-128, 2017, doi: 10.1016/j.media.2017.01.009.

[15] J. Harefa, A. Alexander, and M. Pratiwi, "Comparison classifier: support vector machine (SVM) and K-nearest neighbor (K-NN) in digital mammogram images," *Jurnal Informatika dan Sistem Informasi,* vol. 2, no. 2, pp. 35-40, 2016.

[16] S. K. Ghosh, A. Mitra, and A. Ghosh, "A novel intuitionistic fuzzy soft set entrenched mammogram segmentation under multigranulation approximation for breast cancer detection in early stages," *Expert Systems with Applications,* vol. 169, p. 114329, 2021, doi: 10.1016/j.eswa.2020.114329.

[17] M. A. Al-Antari *et al.*, "An automatic computer-aided diagnosis system for breast cancer in digital mammograms via deep belief network," *Journal of Medical and Biological Engineering,* vol. 38, pp. 443-456, 2018, doi: 10.1007/s40846-017-0321-6.

[18] Y. Qiu *et al.*, "A new approach to develop computer-aided diagnosis scheme of breast mass classification using deep learning technology," *Journal of X-ray Science and Technology,* vol. 25, no. 5, pp. 751-763, 2017, doi: 10.3233/XST-16226.

[19] V. Rajinikanth, S. Kadry, D. Taniar, R. Damaševičius, and H. T. Rauf, "Breast-cancer detection using thermal images with marine-predators-algorithm selected features," in *2021 seventh international conference on bio signals, images, and instrumentation (ICBSII)*, 2021: IEEE, pp. 1-6, doi: 10.1109/ICBSII51839.2021.9445166.

[20] M. Heath *et al.*, "Current status of the digital database for screening mammography," in *Digital Mammography: Nijmegen, 1998*: Springer, 1998, pp. 457-460, doi: 10.1007/978-94-011-5318-8_75.

[21] P. Oza, P. Sharma, S. Patel, and P. Kumar, "Deep convolutional neural networks for computer-aided breast cancer diagnostic: a survey," *Neural computing and applications,* vol. 34, no. 3, pp. 1815-1836, 2022, doi: 10.1007/s00521-021-06804-y.

[22] R. Terzi, *et al.* "The digital eye for mammography: deep transfer learning and model ensemble based open-source toolkit for mass detection and classification," *Signal, Image and Video Processing*, vol. 19, no. 1, p. 170, 2025.

[23] N. Waisi, N. Abdullah, and M. Ghazal, "The Automatic Detection of Underage Troopers from Live-Videos Based on Deep Learning," *Przeglad Elektrotechniczny*, vol. 97, no. 9, 2021, doi: 10.15199/48.2021.09.18.

[24] M. Tan and Q. V. Le, "Efficientnet: Improving accuracy and efficiency through automl and model scaling," *arXiv preprint arXiv:1905.11946*, vol. 2, no. 5, p. 11, 2019.
[25] M. Tan and Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," in *International conference on machine learning*, 2019: PMLR, pp. 6105-6114.
[26] V. Krishna Adithya *et al.*, "EffUnet-SpaGen: an efficient and spatial generative approach to glaucoma detection," *Journal of Imaging*, vol. 7, no. 6, p. 92, 2021, doi: 10.3390/jimaging7060092.
[27] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.
[28] M. M. Abdulghani, M. T. Ghazal, and A. B. M. Salih, "Discover human poses similarity and action recognition based on machine learning," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 12, no. 3, pp. 1570-1577, 2023, doi: 10.11591/eei.v12i3.4930.
[29] R. Albasrawi, F. F. Fadhil, and M. T. Ghazal, "Driver drowsiness monitoring system based on facial Landmark detection with convolutional neural network for prediction," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 11, no. 5, pp. 2637-2644, 2022, doi: 10.11591/eei.v11i5.3966.

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