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(Research Article)

Classification of BI-RADS using convolutional neural network and effecientNet-B7

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Abstract

From its development, image processing technology has become increasingly complex, such as detecting cancer in an image. In this context, the American College of Radiology (ACR) has developed a standard format and terminology called the breast imaging reporting and data system (BI-RADS). The aim of this research is to determine whether CNN can classify BI-RADS types (C1, C2, C3, C4), the best model, and the classification results of BI-RADS types on mammograms using CNN, and the best values for accuracy, sensitivity, specificity, and precision. Google Colaboratory and machine learning libraries were used in this research to create machine learning for BI-RADS classification. Then, a dataset from Kaggle titled "Mini-DDSM: Mammography-based Automatic Age Estimation" by Lekamlage et al., from the Association for Computing Machinery (ACM), Kyoto, Japan, was utilized. Based on the research, an accuracy of 85.9% was achieved for Category 1 classification. Category 2 classification attained an accuracy of 77.9%. The accuracy for Category 3 classification was 81.4%, and for Category 4, it reached 90.8%.

Keywords: BI-RADS; Convolutional Neural Network; Mammography; Google Colaboratory and machine learning

1. Introduction

Currently, breast cancer accounts for 1 in 8 cancer diagnoses, with a total of 2.3 million new cases in both sexes combined [17]. Breast cancer is the most frequently diagnosed cancer in women in 2020, accounting for a quarter of all cancer cases in women. Its prevalence continues to increase, especially in countries in transition. [10]. In 2020 about 685,000 women are estimated to lose their lives due to breast cancer, this figure is equivalent to 16%, representing 1 in every 6 cancer-related deaths in women. The recent launch of the Global Breast Cancer Initiative by the World Health Organization (WHO) is a response to previously inadequate public health measures in addressing this problem [2]. Cancer appears in the human body due to the abnormal development of tumor cells, causing invasion of the surrounding tissue.

After 10 years have passed, Deep learning already made significant progess in research and the subject of healthcare in medical images [7]. In the research on breast cancer, which produced encouraging findings as well, several deep architectures [9] are investigated and effectively applied. The use of computer-aided diagnostics to diagnose breast cancer is still being studied by a sizable number of researchers. In a hybrid Convolutional Neural Network (CNN) approach presented by Arevalo et al. [3], handmade image-based features are learned using supervised learning techniques.

score system in the Breast Imaging Data and Reporting (BI-RADS) useful for identifying the type of breast cancer. Clinically, BI-RADS provides a criteria and guidance for doctor or physicians to identify the categories of breast cancer againts on clinical images [1]. BI-RADS was created by The American College of Radiology in an effort to create a language for reporting mammography and assessing findings [1]. The goals of BI-RADS are to make a standard of

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imaging report, decrease the confusion in clinical images reading by making a language that radiologists understand and among imaging testing, develop communication that doctors can use to comprehend significant findings related to existing images and data, aiding in the monitoring of results. [12]. BI-RADS is the most important part of an imaging report. with the system, the entire report must commence with depiction of the overall in the breast composition [16]. This research can contribute to improved screening on breast and early diagnosis masses of breast, preventing surgical procedure. It can also enhance the efficiency of patient follow-ups in cases of breast malignancy [8]. BI-RADS have seven categories from 0 to 6, if the number is higher, more higher the level of malignancy [4,16].

A widely used machine learning approach is deep learning, in which a computer model directly classifies information by learning from text, sound, or images. [14]. These models have undergone training on diverse datasets and CNN architectures featuring multiple layers [20]. deep learning automatically detects cancer cells from the medical images [5].

The Convolutional Neural Network (CNN) is a neural network type widely employed for processing image data. CNNs are employed to detect and identify objects within an image [19]. CNN comprises neurons possessing weights, biases, and functions of activation. The convolutional layer is composed of neurons organized to create a filter with a specific height and length (pixels). [15,18].

In the study conducted by Huang et al. [11] titled "Two-stage CNNs for computerized BI-RADS categorization in breast ultrasound images," they developed several models for classifying BI-RADS in ultrasound images using CNN, ResNet, and Visual Geometry Group (VGG). In the classification process, ResNet achieved an accuracy of 75.5%, VGG achieved an accuracy of 72.3%, and CNN achieved an accuracy of 79.7% for BI-RADS category 3. From these accuracy results, it can be concluded that CNN excels in classifying images. Therefore, this study implements the CNN method as a detector for BI-RADS types. The CNN method is expected to be useful in determining BI-RADS types, thus reducing the number of cancer cases.

2. Methodology

Research on the classification of BI-RADS on mammography image using machine learning algorithms was conducted at the Biophysics and Medical Physics Laboratory in the Physics Study Program at Udayana University. The dataset utilized in this research, sourced from Kaggle, comprises 4191 mammography images classified under BI-RADS categories C1, C2, C3, and C4. This data contains data taken from the 3rd International Conference on Digital Medicine and Image Processing (DMIP 2020) article titled "Mini-DDSM: Mammography-based Automatic Age Estimation" by Lekamlage, et al from the Association for Computing Machinery (ACM), Kyoto, Japan [6,13].

In this research, Google Colaboratory software was used for the creation of the BI-RADS classifier model. Libraries in Python programming facilitate the development of applications in machine learning. The creation of the machine learning model in this research utilized several libraries, namely NumPy, Pandas, TensorFlow, Keras, Matplotlib, and Seaborn. This research utilized a laptop with the following specifications: Intel Core i5 processor, 16GB RAM, and Intel Iris integrated graphics. In this research, the initial step involved the classification of objects into four BI-RADS categories: C1, C2, C3, and C4, using the Convolutional Neural Network (CNN) algorithm. The main process in creating the database included training the data, aiming to achieve high accuracy values during the object detection process.

Data preprocessing involves entering or consolidating data into the dataset model under creation. The dataset, sourced from Kaggle, encompasses 4191 Mammography images categorized with BI-RADS classifications C1, C2, C3, and C4. During the data preprocessing phase, the data is partitioned into training and testing sets. Following the preprocessing of the data, the construction of a machine learning model commences. During this stage, hyperparameters are adjusted based on the available data and specific challenges. Once the model is constructed, the training process ensues, enhancing the model's capability to classify Mammography image data in alignment with the assigned labels. Subsequently, the model's training results are evaluated. If there is room for improvement in model accuracy, optimization can be achieved by refining the hyperparameters utilized in the model of machine learning. The procedure of research is illustrated in Fig. 1.

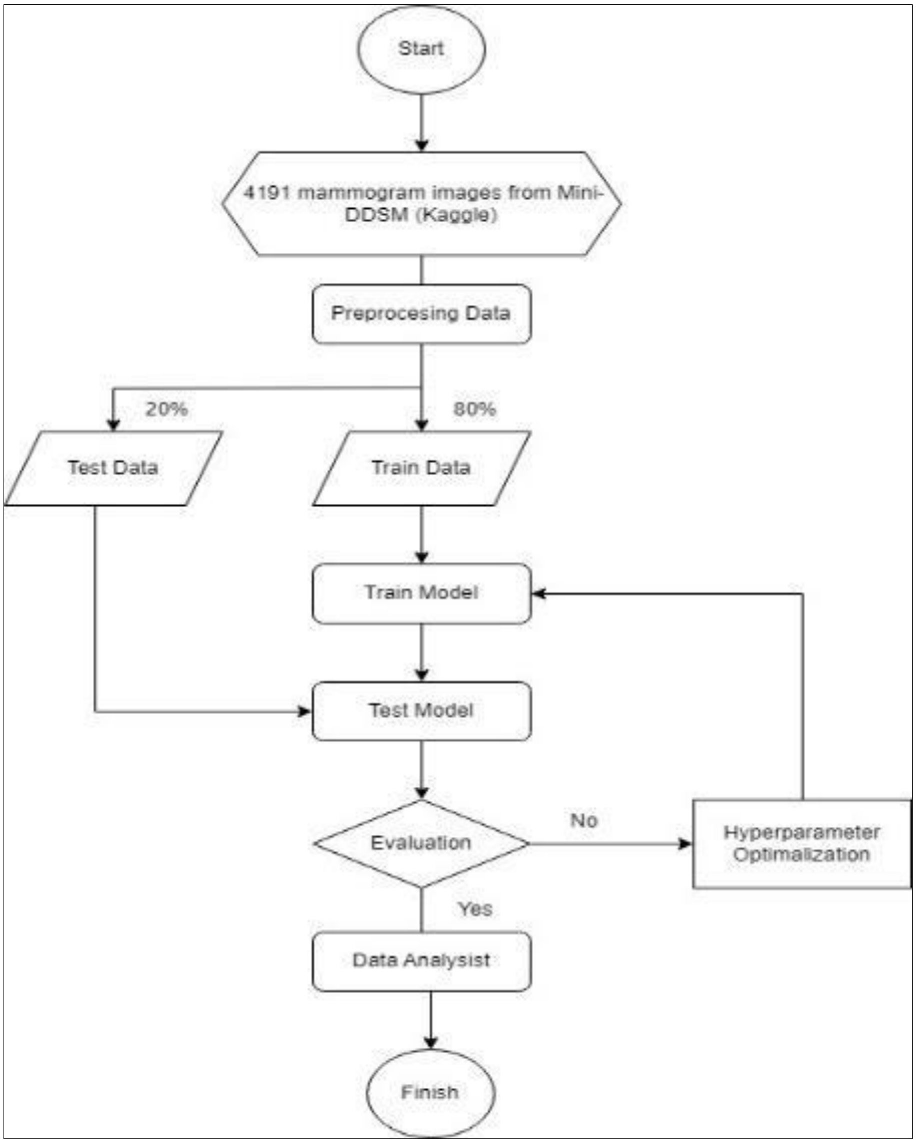

Figure 1 Research procedure

3. Results and discussion

3.1. Model architecture

The model of CNN illustrated comprises a starting model employing transfer learning of EfficientNetB7, as depicted in Fig. 2. EfficientNetB7 demonstrates commendable performance with modest computational requirements. EfficientNetB7 has a high number of parameters, around 66 million, accompanied by a high accuracy value. Subsequently, modifications were made to some convolutional layers (Convolutional2D) and pooling layers (MaxPooling2D), designed for processing image data. This layer's function involves recognizing Using the Rectifier Linear Unit (ReLU) activation function, pictures are generated based on their pixels. In this stage, 8 filter parameters are imported, indicating that 8 filters with a size of 3x3 (kernel_size = (3, 3)). are applied in the convolution process. The second layer introduces 16 filter parameters, while the third layer involves 32 filters, for the fourth layer involves 64 layers and the fifth layer employs 128 filter parameters. The input_shape for all layers is set at (200, 150, 3), signifying that all input images must be 200x150 pixels in size with three color layers in matrix form. The function in ReLU activation is uniformly applied across all layers, given its common usage in CNNs. Additionally, a MaxPooling2D layer is incorporated to reduce image resolution while retaining essential information. The MaxPooling2D layer operates by selecting the greatest value from the processed data, and a 2x2 pooling size is used in the first layer. The smaller feature maps in this setup speed up the analysis time.

The output from this fifth layer, which serves as feature maps, is converted into a single layer using the flatten technique. Flattening transforms all matrices into a single vector, which is useful for the input to the neural network. Next, a Dense layer is applied. This Dense or hidden layer is sized 1024 in the first layer, containing 1024 neurons. It is followed by the parameter activation='relu'. Subsequently, a dropout is implemented to prevent overfitting of the data. The next step involves a hidden layer with 512 neurons and the activation parameter set to 'relu'. Another dropout is applied to prevent overfitting of the data. The subsequent step involves defining the output layer, where the 4 categories (C1, C2, C3, C4) are represented by 4 neurons corresponding for the labels in the dataset.

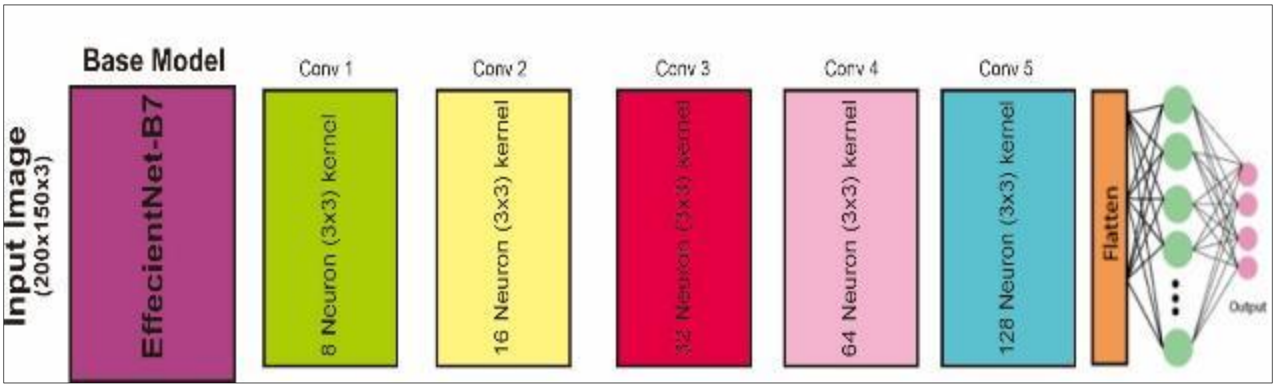

Figure 2 Architecture Model

3.2. Confusion matrix

fig. 3 is the outcome of accuracy across multiple classes. The number of comparison results between the predictions of a machine learning algorithm and the actual results (ground truth) is displayed in the figure. 123 true positive results for C1, 132 true positive results for C2, 146 true positive results for C3, and 246 true positive results for C4 were acquired from the images.

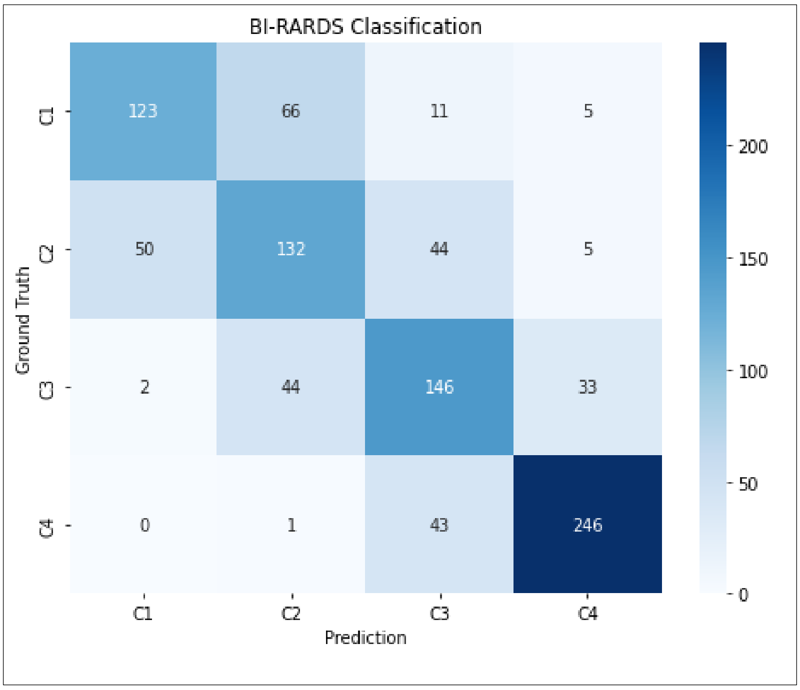

Figure 3 Confusion matrix result

3.3. Precision, sensitivity, specificity and accuracy

The C1 labeling results showed a precision of 0.702, sensitivity of 0.600, specificity of 0.930, and accuracy of 0.859. For label C2, the precision is 0.543, the sensitivity is 0.571, the specificity is 0.846, and the accuracy is 0.814. For label C3, the precision is 0.598, the sensitivity is 0.648, the specificity is 0.865, and the accuracy is 0.814. Finally, for label C4, the precision is 0.851, the sensitivity is 0.848, the specificity is 0.930, and the accuracy is 0.908.

Table 1 Table result of precision, sensitivity, specificity and accuracy

Clasification	Precision	Sensitivity	Spesificity	Accuracy
C1	0.702	0.600	0.930	0.859
C2	0.543	0.571	0.846	0.779
C3	0.598	0.648	0.865	0.814
C4	0.851	0.848	0.930	0.908

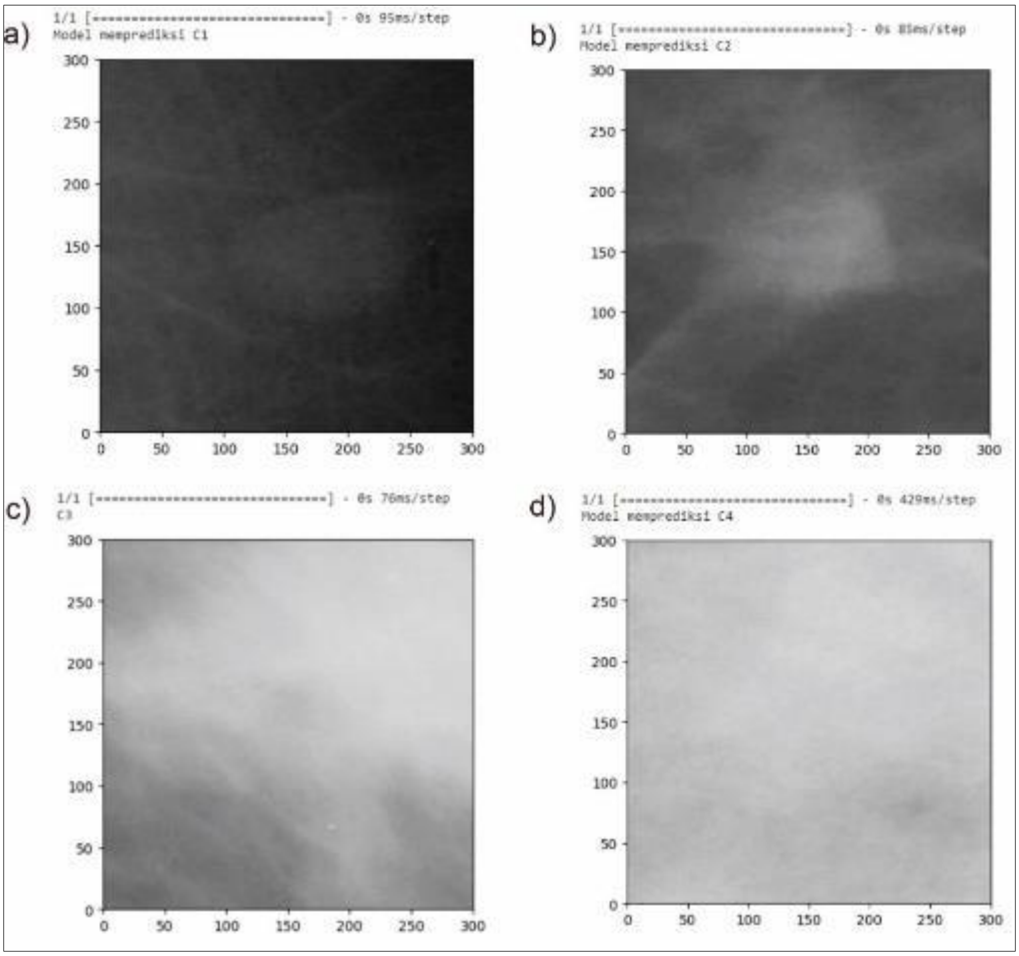

Figure 4 Result of predicted BI-RADS

Figure 4 displays the result of predicted BI-RADS. The model defines BI-RADS classifications as C1, C2, C3, and C4, and successfully detects them. The prediction results for the Mammography image are presented as an image with dimensions of 200×150 and 3 RGB colour channels. The classification prediction yields an overall accuracy of 68%.

4. Conclusion

The objectives in research is to improve of the precision or accuracy in categorizing BI-RADS, aiming to assist doctors in identifying specific brain tumors. This represents the first comprehensive evaluation of grading on mammography picture with the BI-RADS category. Utilizing an architecture of CNNs that can learn autonomously and extracting features in images, the created system can accurately identify in categorizing BI-RADS at mammography images. With assessment model on the system can achieve a BI-RADS category 4 score, encompassing C 1, C2, C3, and C4. This has the potential to alleviate the process of reviewing images that takes amount of time and reduce the impact of a doctor's experience in medical practice. Furthermore, in creating a categorization system, it can get good and effective categorization features with an automatic category feature system. Through the application of transfer learning using the EfficientNetB7 model, an accuracy of 85.9% was achieved for Category 1 classification. Category 2 classification attained an accuracy of 77.9%. The accuracy for Category 3 classification was 81.4%, and for Category 4, it reached 90.8%. Utilizing EfficientNetB7 for BI-RADS classification proves to be an effective means to enhance the diagnostic accuracy of BI-RADS categories.

Compliance with ethical standards

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Disclosure of conflict of interest

The Authors proclaim no conflict of interest.

References

[1] American College Of Radiology. Bi-Rads Committee. (2013). ACR BI-RADS atlas breast imaging and reporting data system. Reston, Va: American College Of Radiology.

[2] Anderson, B. O., Ilbawi, A. M., Fidarova, E., Weiderpass, E., Stevens, L., Abdel-Wahab, M., & Mikkelsen, B. (2021). The Global Breast Cancer Initiative: a strategic collaboration to strengthen health care for non-communicable diseases. The Lancet Oncology, 22(5), 578–581. https://doi.org/10.1016/S1470-2045(21)00071-1

[3] Arevalo, J., González, F. A., Ramos-Pollán, R., Oliveira, J. L., & Guevara Lopez, M. A. (2016). Representation learning for mammography mass lesion classification with convolutional neural networks. Computer Methods and Programs in Biomedicine, 127, 248–257. https://doi.org/10.1016/j.cmpb.2015.12.014

[4] Bartolotta, T. V., Orlando, A. A. M., Di Vittorio, M. L., Amato, F., Dimarco, M., Matranga, D., & Ienzi, R. (2020). S-Detect characterization of focal solid breast lesions: a prospective analysis of inter-reader agreement for US BI-RADS descriptors. Journal of Ultrasound, 24(2), 143–150. https://doi.org/10.1007/s40477-020-00476-5

[5] Charan, S., Khan, M. J., & Khurshid, K. (2018). Breast cancer detection in mammograms using convolutional neural network. https://doi.org/10.1109/ICOMET.2018.8346384

[6] Cheddad, A. (2021, March 23). The Complete Mini-DDSM. Retrieved August 12, 2023, from www.kaggle.com website: https://www.kaggle.com/datasets/cheddad/miniddsm2

[7] Das, H. S., Das, A., Neog, A., Mallik, S., Bora, K., & Zhao, Z. (2023). Breast cancer detection: Shallow convolutional neural network against deep convolutional neural networks based approach. Frontiers in Genetics, 13. https://doi.org/10.3389/fgene.2022.1097207

[8] Ghaemian, N., Haji, N., Tehrani, G., Nabahati, M., & Hospital, S. (2021). Accuracy of mammography and ultrasonography and their BI-RADS in detection of breast malignancy. Caspian Journal of Internal Medicine, 12(4), 573–579. https://doi.org/10.22088/cjim.12.4.573

[9] Hamidinekoo, A., Garzón-Martínez, G. A., Ghahremani, M., Corke, F., Zwiggelaar, R., Doonan, J. H., & Lu, C. (2020). DeepPod: a convolutional neural network based quantification of fruit number in Arabidopsis. GigaScience, 9(3). https://doi.org/10.1093/gigascience/giaa012

[10] Heer, E., Harper, A., Escandor, N., Sung, H., McCormack, V., & Fidler-Benaoudia, M. M. (2020). Global burden and trends in premenopausal and postmenopausal breast cancer: a population-based study. The Lancet Global Health, 8(8), e1027–e1037. https://doi.org/10.1016/s2214-109x(20)30215-1

[11] Huang, Y., Han, L., Dou, H., Luo, H., Yuan, Z., Liu, Q., … Yin, G. (2019). Two-stage CNNs for computerized BI-RADS categorization in breast ultrasound images. Biomedical Engineering Online, 18(1). https://doi.org/10.1186/s12938-019-0626-5

[12] Lee J. Practical and illustrated summary of updated BI-RADS for ultrasonography. Ultrasonography. 2017 Jan 1;36(1):71–81.

[13] Lekamlage, C. D., Afzal, F., Westerberg, E., & Chaddad, A. (2020). Mini-DDSM: Mammography-based Automatic Age Estimation. 2020 3rd International Conference on Digital Medicine and Image Processing. https://doi.org/10.1145/3441369.3441370

[14] Rawat, W., & Wang, Z. (2017). Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review. Neural Computation, 29(9), 2352–2449. https://doi.org/10.1162/neco_a_00990

[15] Saber, A., Sakr, M., Abo-Seida, O. M., Keshk, A., & Chen, H. (2021). A Novel Deep-Learning Model for Automatic Detection and Classification of Breast Cancer Using the Transfer-Learning Technique. IEEE Access, 9, 71194–71209. https://doi.org/10.1109/access.2021.3079204

[16] Spak, D. A., Plaxco, J. S., Santiago, L., Dryden, M. J., & Dogan, B. E. (2017). BI-RADS ® fifth edition: A summary of changes. Diagnostic and Interventional Imaging, 98(3), 179–190. https://doi.org/10.1016/j.diii.2017.01.001

[17] Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. CA: A Cancer Journal for Clinicians, 71(3), 209–249. Retrieved from https://acsjournals.onlinelibrary.wiley.com/doi/10.3322/caac.21660

[18] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., … Rabinovich, A. (2014). Going deeper with convolutions. Retrieved from arXiv.org website: https://arxiv.org/abs/1409.4842

[19] Tobias, L., Aurelien Ducournau, Rousseau, F., Mercier, G., & Ronan Fablet. (2016). Convolutional Neural Networks for object recognition on mobile devices: A case study. International Conference on Pattern Recognition. https://doi.org/10.1109/icpr.2016.7900181

[20] Devare, M. 2019. Challenges and Opportunities in High-Performance Cloud Computing. Handbook of Research on the IoT, Cloud Computing, and Wireless Network Optimization