2024 IEEE International Conference on Contemporary Computing and Communications (InC4)

Breast Cancer Image Classification: Leveraging Deep Learning and Large Language Models for Semantic Integration

K.K.Harini[1], R.Nandhini[2], A.M.Rajeswari[3], R.Deepalakshmi[4]
Department of Computer Science and Engineering
Velammal College of Engineering and Technology
Madurai, India
[1]harinikarthikeyan22@gmail.com, [2]nandhinicsea@gmail.com, [3]amrtce@gmail.com, [4]rdl@vcet.ac.in

2024 IEEE International Conference on Contemporary Computing and Communications (InC4) | 979-8-3503-8365-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/INC460750.2024.10649116

***Abstract*—Breast cancer, a significant global health problem that is mainly affecting women, demonstrates the importance of early detection to enhance survival rates. Medical image classification is a significant field that utilizes deep learning methods such as Convolutional Neural Networks (CNNs), Region-Based CNNs (R-CNNs), and Deep Neural Networks (DNNs). Despite this, challenges such as over fitting persist, particularly with limited data or complex models. Although these models learn hierarchical features, interpreting them in intricate image structures is still challenging and complicates decision rationale. To address this, we propose a comprehensive approach for breast cancer image classification. The initial process involves image segmentation using CNN to identify regions of interest, followed by precise object detection with OpenCV. Data quality and diversity are ensured by preprocessing and augmentation with ImageDataGenerator, while informative features are extracted using the InceptionV3 model. Our analysis of textual descriptions and embeddings is done by integrating Sentence Transformers and CLIP from the Large Language Model (LLM) framework. Achieving robust decision-making is ensured by setting a threshold of 0.7 for image classification based on predicted malignancy probability. Finally, improving the computations of similarity scores can improve prediction accuracy for reliable diagnostic interpretations. An accuracy of 0.92 in breast cancer diagnosis is guaranteed by integrating LLM and CNN for classification.**

Keywords—Breast Cancer, Image Classification, Machine Learning, Deep Learning, LLM.

I. Introduction

Breast cancer refers to the disease in which abnormal breast cells grow out of control and form tumors. Unchecked tumor growth can lead to fatal consequences throughout the body. The number of breast cancer diagnoses in 2020 was 2.3 million women, and 685,000 deaths took place worldwide. In the past 5 years, breast cancer has been diagnosed to 7.8 million women, making it the most prevalent cancer worldwide, as of the end of 2020 [1]. The survival of breast cancer has improved since the 1990s when countries introduced early detection and comprehensive treatment programs that included effective medical therapies.

Although breast cancer can be detected once symptoms appear, many women with breast cancer do not experience any symptoms. Regular breast cancer screening is an essential part of prevention. Early detection has been aided by mammography screening [2] which has resulted in a 20% decrease in mortality rates. In cases where the breast tissue is dense and malignancies are difficult to detect, its effectiveness may be limited. A shocking revelation has emerged that 25% of women diagnosed with breast cancer receive a negative screening result within two years.

A. The Breast Cancer Data Set

The diagnosis and prognostic landscape of breast cancer are heavily dependent on intricate microscopic representations of tissue samples stained for meticulous examination in breast histopathology images. Fig. 1 and Fig. 2 deliberate the levels of breast cancer infection. By providing detailed insights into tissue morphology, these images provide valuable information for critical decisions in patient care. A benign tumor, as depicted in Fig. 1 generally does not invade or spread and has distinct, smooth, and regular borders. Whereas the malignant cells as in Fig. 2 have a higher chance of metastasizing or spreading to other parts of the body. The publicly available Breast Histopathology Images Dataset from Kaggle [3] is used in this study to obtain microscope slide images of breast cancer (BCa) specimens at 40x magnification. The use of this dataset is crucial for research and model development that aim to enhance breast cancer diagnostic capabilities [4].

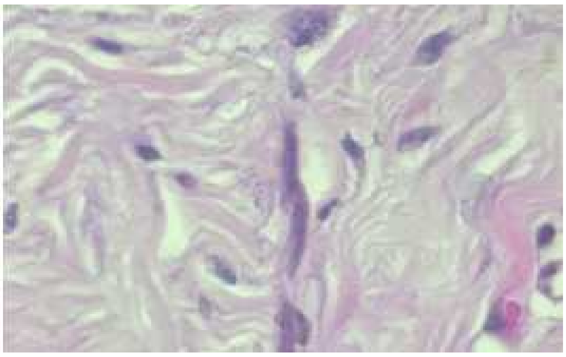


Fig. 1. Benign tumors.

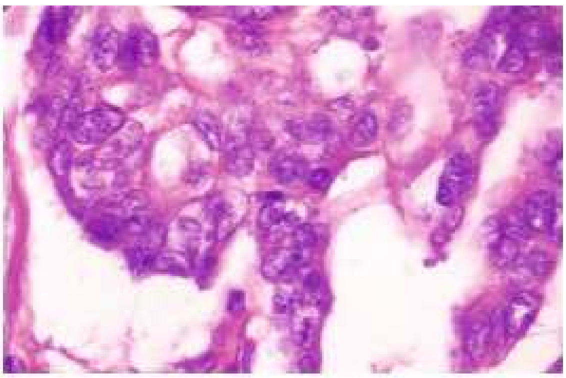


Fig. 2. Malignant tumors

The field of Artificial Intelligence (AI), especially within the scope of Machine Learning (ML) and Deep Learning

Authorized licensed use limited to: b-on: UNIVERSIDADE NOVA DE LISBOA. Downloaded on July 12,2025 at 22:05:21 UTC from IEEE Xplore. Restrictions apply.

(DL), has made significant progress in recent epochs [5], [6], [7]. Predictive analytics for images has been dominated by ML and DL, which are prominent aspects of AI. The extraction of insights from data is accomplished through sophisticated algorithms, which uncover valuable knowledge and patterns.ML and DL have become a crucial tool for prognosticating a variety of illnesses, including breast cancer, within the healthcare field.

B. Image classification using machine learning approaches

Image classification is accomplished through the use of traditional machine learning algorithms like Support Vector Machines, Random Forest, and others [5], [8]. In recent years, techniques such as the Histogram of Oriented Gradients combined with Support Vector Machines have become more popular [5], [8]. Understanding the strengths and limitations of traditional methods for image classification is crucial. The effectiveness of these conventional methods is demonstrated in specific aspects. Using these methods for image classification tasks has its limitations that become apparent.

There are some downsides in using traditional machine learning algorithms for image classification [6], such as:

- Reliance on Manual Feature Crafting: The quality of manually crafted features is closely associated with overall performance in traditional algorithms. The task of designing meaningful features for image classification is challenging, but it might not fully capture the intricacies of image data.
- Challenges with High-Dimensional Data: Images are a type of high-dimensional data, and traditional algorithms may face challenges when confronted with multiple features. These algorithms may find it tough to generalize from training data to unseen images as a result of the 'curse of dimensionality.
- Inability to Capture Spatial Hierarchies: Spatial hierarchies and relationships in images may not be captured by traditional algorithms, which are essential for comprehending visual content.
- Sensitivity to Transformations: There are traditional algorithms that can be influenced by transformations, such as translations, rotations, and images.
- Manual Feature Engineering Demands: The necessity of manually engineering features is a significant drawback, as it often requires domain expertise and is time-consuming.
- Limited Capacity for Pattern Recognition: Intricate patterns and relationships within data may be difficult for traditional algorithms to discern.

Deep learning has become the paradigm of choice to address these challenges, as it has demonstrated remarkable success in image classification tasks. Autonomous acquisition of hierarchical features from data can be achieved by deep learning models [9]. The performance of conventional methods has been exceeded by eliminating the need for manual feature engineering in deep learning approaches, which revolutionized image classification.

C. Deep learning approaches for image classification

Artificial neural networks with multiple layers facilitate automatic feature extraction in deep learning, which is a subset of machine learning inspired by the structural intricacies of the human brain. The ability of models to autonomously identify relevant features is enabled by its proficiency in representation learning, which eliminates the need for manual engineering. A significant amount of labeled data for training is essential to the effectiveness of this approach [5], [9]. Both supervised and unsupervised tasks use DLs extensively. Despite the long-standing challenges of interpretability and computational demands, DL has consistently demonstrated remarkable performance in image processing, labeled data processing, and various domains. Deep learning is emerging as a transformative force in breast cancer image classification, which significantly improves diagnostic accuracy and efficiency [9]. Hierarchical feature extraction is the key role of Convolutional Neural Networks (CNNs) [10], which are notable for their proficiency.

The document's remaining sections are arranged as per the following method. Literature from similar studies is described in Section 2. The proposed method's framework and principles of operation are discussed in Section 3. In section 4, we discuss the proposed work's results, and finally, in section 5, we provide a summary of the LLMs.

II. RELATED WORK

Jia et al. [11] suggested the use of the WOA-SVM algorithm to adjust support vector machine parameters in a sequential manner. Breast cancer recognition accuracy is significantly enhanced by the use of the WOA-SVM algorithm, which is a significant advantage. Wang et al. created a hybrid CNN-GRU model [12] that is designed to automatically categorize IDC tissue images. This hybrid model has been developed to enhance classification accuracy and efficiency in detecting IDC tissue. The introduction of a model [13] that combines artificial neural networks and an additional tree classifier is noteworthy. One of the main strategies is transfer learning [14], which fine-tunes pre-trained models from ImageNet to adapt to breast cancer features. The coordinated Attention Mechanisms [15] demonstrate the importance of attention mechanisms in pinpointing relevant regions, thus improving diagnostic precision. Model robustness is ensured by techniques such as data augmentation [16], and model interpretation in clinical contexts is facilitated by explainability methods. By integrating deep learning into healthcare systems, automated and accurate breast cancer diagnosis can be simplified, enabling healthcare professionals to make timely decisions. Deep learning is a force that is transformative in the classification of breast cancer images [17].

Histological grading of breast cancers was accomplished by the authors [18] through the use of DeepGrade, a deep learning-based approach. Wienmed filter preprocessing was used by the authors [19] to develop a novel BPBRW using the HKH-ABO approach. Sharma et al. [20] proposed a novel 'end-to-end' method that includes pre-training on local image patches and fine-tuning on datasets without Region of Interest (ROI) annotations. Incorporating the Coordinated Attention Mechanism into the DenseNet architecture is the new approach presented by the authors [21]. As a result of this integration, the CA-BreastNet model was created to categorize different types of breast cancer using the BreakHis dataset. By developing a hybrid CNN-LSTM model [22], the authors presented a new approach.

Authorized licensed use limited to: b-on: UNIVERSIDADE NOVA DE LISBOA. Downloaded on July 12,2025 at 22:05:21 UTC from IEEE Xplore. Restrictions apply.

TABLE I. STATE OF ART OF EXISTING METHODS FOR BREAST CANCER CLASSIFICATION.

Existing Method	Accuracy (%)	Strength of the method	Limitation
Deep Neural Network (DNN) [12]	86.00	Multiple layers enable hierarchical learning.	Over fitting.
Artificial Neural Networks (ANN) [13]	99.41	Flexibility in architecture design.	Proper preprocessing of image data is crucial.
Hybrid Algorithms [19]	99.64	Strengths of multiple models.	Inherently more complex than single-model approaches and over fitting may arise.
Transfer Learning (Deep Learning Model) [20]	98.40	I am saving computational resources and effective generalization to new, unseen data.	They are struggling to adapt to entirely new concepts.
Convolutional Neural Network (CNN) [21]	97.59	Automate hierarchical feature learning.	Long-range dependencies and understanding the global context within the data.
Recurrent Neural Network (RNN) [24]	95.18	Capturing sequential dependencies.	Less adept at understanding spatial relationships in images.
Deep Neural Network (DNN) [12]	86.00	Multiple layers enable hierarchical learning.	Over fitting.

To classify subtypes of benign and malignant breast cancer histopathological images, this model employs transfer learning with ImageNet weights. Patel et al. [23] Showcase GARL-Net, which incorporates transfer learning by using DenseNet121 as the backbone network. Saleh et al. [24] concentrated their efforts on designing an optimized deep neural network model that incorporates feature selection and the Keras-Tuner optimization technique. Furthermore, Transfer Learning [25] has become a standard approach, in which pre-training on annotated datasets is followed by fine-tuning on datasets that don't have Region of Interest (ROI) annotations. Breast cancer classifications are made more robust by leveraging knowledge gained from annotated datasets through this approach. Thus the advantages of deep learning include increased accuracy and efficiency, while also addressing the challenges that are inherent in traditional machine learning methodologies.

Table I analysis shows that there are various advantages and disadvantages associated with every algorithm used for breast cancer image classification. Over fitting, computational intensity, and the need for meticulous hyper parameter tuning are common drawbacks of these algorithms [26]. CNNs may encounter difficulties when dealing with limited data, RNNs with lengthy dependencies, DNNs with disappearing / exploding gradients, and ANNs with sequential data. Task / domain shifts are challenging for transfer learning, whether it's in deep learning or traditional contexts. Although hybrid algorithms may have unique advantages, they also introduce complexity and interpretability issues, which affect implementation and deployment.

The complexities inherent in deep learning [27] necessitate that an ideal algorithm strike a balance between efficiency, robustness, and adaptability, considering these challenges. This comprehensive approach is vital in the development of breast cancer image classification models that are not just precise and reliable, but also efficient, adaptable, and resilient in real-world applications.

III. PROPOSED METHOD

By leveraging the multimodal capabilities, LLMs offer a transformative approach in image classification [28]. In order to overcome the shortfalls of traditional ML and DL algorithms in image classification, large language models (LLMs) [29] like CLIP (Contrastive Language-Image Pre-training) are employed along with a sentence transformer. CLIP, which is based on LLM, comprehends both images and text, making it possible to accurately predict the chances of malignancy and categorize it as either 'Malignant' or 'Benign' with a threshold of 0.7. CLIP is different from traditional models in that it processes images and text simultaneously, creating a joint embedding space for meaningful representation. The effectiveness of implementation can be enhanced by integrating CLIP multimodal capabilities into image classification tasks. CLIP's role is to enhance semantic understanding of visual content by interpreting and generating textual descriptions. Optimization of image classification is achieved through a collaborative approach, with CLIP playing a key role. The strategic selection of a threshold is meant to balance computational latency caused by dataset imbalances and guarantee efficient processing for both malignant and benign images.

The Fig. 3 illustrates how LLM functions. The LLM model utilizes Long Short Term Memory (LSTM) for the purpose of training image models.

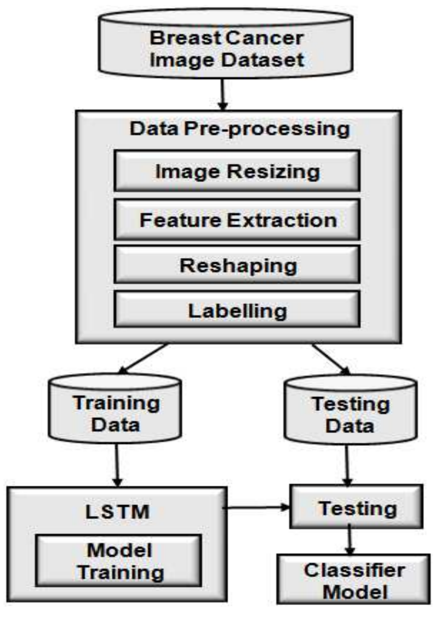
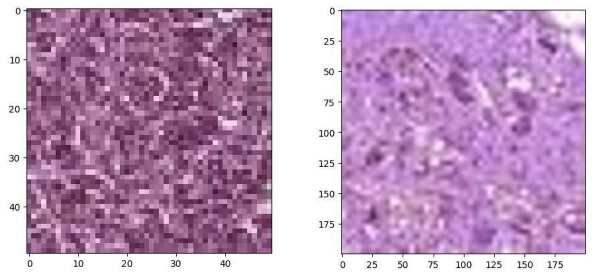


Fig. 3. Framework for the proposed LLM

Authorized licensed use limited to: b-on: UNIVERSIDADE NOVA DE LISBOA. Downloaded on July 12,2025 at 22:05:21 UTC from IEEE Xplore. Restrictions apply.

A. Image segmentation

In the initial segmentation step [30], it is necessary to precisely separate regions of interest, such as tumors or lesions, in the images. To delineate and identify specific areas within the images that are relevant to the classification task, segmentation is crucial. Segmentation enables the precise identification of regions of interest and the subsequent analysis to concentrate on these specific areas. This targeted approach improves the model's ability to make accurate classifications. Consistent analysis is achieved by using uniform image sizes due to rescaling as in Fig. 4.



(a) Before (b) After

Fig. 4. Malignant tumors befor and after segmentation & rescaling

Detecting objects [31] aids the model in comprehending and creating textual descriptions for the structures identified in the pictures. LLMs are able to improve their understanding of anomalies in spatial distribution and context by taking this step. Textual information provided by them becomes richer and more contextually relevant as a result. Detection and evaluation of potential malignancies in medical images can be enhanced by employing object detection in LLMs. Training and evaluating a CNN for binary image classification is a part of the data modeling process, which involves using convolutional layers and max-pooling for feature extraction. By augmenting data, the Image Data Generator improves performance, which is assessed using accuracy metrics. Understanding text and image content is made accurate by embedding techniques like CLIP and Sentence Transformer.

B. Image mapping and labelling

Preprocessing using Python packages, including those inherent to LLM, is necessary for mapping labels to images. The primary tasks are to use 'Image Data Generator' to preprocess images for rescaling and augmentation, and to encode text with 'sentence_transformers' to link textual descriptions with image labels. The 'JSON' module is responsible for managing descriptions, while the 'numpy' module facilitates numerical operations. The 'tensorflow.keras.applications.inception_v3' is employed for the extraction of features from images. The data preparation and model training for multimodal learning tasks are streamlined. A sample labeled image is shown in the Fig. 5.

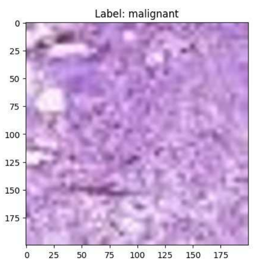


Fig. 5. Malignant tumors image mapping and labelling

C. Image prediction

The prediction process involves preprocessing where user-uploaded images are resized to a standardized format of 200 x 200 pixels. The LLM and a sentence transformer work together to perform this resizing. Images are classified as 'Malignant' or 'Benign' by the model, which uses a threshold of 0.7 to predict malignancy probability. The threshold is determined through trial and error, as outlined in Table II. To manage computational latency caused by dataset imbalances, this threshold was strategically chosen. Optimizing the computations of similarity scores between images and class descriptions can improve prediction accuracy while also ensuring operational efficiency.

TABLE II. FIXATION OF THRESHOLD VALUE

Threshold	Prediction	Latency (Malignant)	Latency (Benign)	Similarity Score
< 0.7	Malignant	High	Low	Not optimal
> 0.7	Benign	Low	High	Optimal
0.7	Borderline	Balanced	Balanced	Balanced

IV. RESULTS AND DISCUSSIONS

CLIP and Sentence Transformer models are utilized in the proposed work to examine the impact of dataset size on image classification using LLM. The importance of sufficient training data is evident in the results, which consistently demonstrate improved accuracy and reduced loss with larger datasets. Preprocessing and feature extraction are enhanced by CLIP and Sentence Transformer models, which play a key role. The significance of LLM in selecting datasets and improving image classification effectiveness is highlighted by these findings. According to the performance metrics presented in the Table III, LLM is crucial in optimizing dataset selection and improving image classification efficacy, as evidenced by these findings. The importance of abundant training data for effective LLM model training and diagnostic interpretation is highlighted by the correlation between increased dataset size and improved accuracy and reduced loss.

TABLE III. FIXATION OF THRESHOLD VALUE

Dataset Size	Accuracy	Loss
25 %	0.7652	0.5648
50 %	0.8400	0.3618
75 %	0.8765	0.3033
100 %	0.9217	0.1996

V. CONCLUSION

The proposed work survey underscores the urgency of addressing breast cancer, especially its disproportionate impact on women, and emphasizes the crucial role of timely detection in increasing survival rates. Deep learning techniques, such as CNN, are crucial for image classification, but they are confronted with challenges such as over fitting. To fight over fitting and improve interpretability, LLM is suggested.

Authorized licensed use limited to: b-on: UNIVERSIDADE NOVA DE LISBOA. Downloaded on July 12,2025 at 22:05:21 UTC from IEEE Xplore. Restrictions apply.

The Large Language Model (LLM) framework's integration of Sentence Transformers and CLIP is suggested as a way to leverage pre-training on diverse data sources. LLM natural language processing capabilities can transform breast cancer image classification, enabling personalized treatment plans and providing explanations that can be easily understood by humans. The threshold of 0.7 has been established through trial and error to improve image classification. Our findings suggest that LLM is essential in optimizing dataset selection and improving image classification efficiency to 0.92 percent.

The introduction of LLM is a significant improvement in overcoming the limitations of traditional deep learning approaches. Additionally, the outcome is improved healthcare outcomes due to the enhancement of interpretability and personalized diagnostic and treatment approaches.

REFERENCES

[1] World Health Organization, Newsroom. (2023, Jul 12). Breast Cancer. https://www.who.int/news-room/fact-sheets/detail/breast-cancer

[2] Reshma, V. K., Nancy Arya, Sayed Sayeed Ahmad, Ihab Wattar, Sreenivas Mekala, Shubham Joshi, and Daniel Krah. "Detection of breast cancer using histopathological image classification dataset with deep learning techniques." BioMed Research International 2022, https://doi.org/10.1155/2022/8363850.

[3] https://www.kaggle.com/datasets/paultimothymooney/breast-histopathology-images. Accessed on Feb 2024.

[4] Janowczyk, Andrew, and Anant Madabhushi. "Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases." Journal of pathology informatics, 2016, Vol 7(1), page 29. https://doi.org/10.4103/2153-3539.186902.

[5] Wang, Pin, En Fan, and Peng Wang. "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning." Pattern Recognition Letters, 2021, Vol. 141, pages 61-67.https://doi.org/10.1016/j.patrec.2020.07.042.

[6] Rabiei, Reza, Seyed Mohammad Ayyoubzadeh, Solmaz Sohrabei, Marzieh Esmaeili, and Alireza Atashi. "Prediction of breast cancer using machine learning approaches." Journal of Biomedical Physics & Engineering, 2022,Vol. 12(3), pages 297–308.https://doi.org/10.31661%2Fjbpe.v0i0.2109-1403.

[7] Nasser, Maged, and Umi Kalsom Yusof. "Deep Learning Based Methods for Breast Cancer Diagnosis: A Systematic Review and Future Direction." Diagnostics, 2023,Vol. 13(1), pages 161-161.https://doi.org/10.3390%2Fdiagnostics13010161.

[8] Lai, Yunfei. "A comparison of traditional machine learning and deep learning in image recognition." In Journal of Physics: Conference Series,IOP Publishing, 2019, Vol. 1314(1), pages 012148. DOI: 10.1088/1742-6596/1314/1/012148.

[9] Li, Yinglong. "Research and application of deep learning in image recognition." In 2022 IEEE 2nd International Conference on Power, Electronics and Computer Applications (ICPECA), 2022, pages 994-999. https://doi.org/10.1109/ICPECA53709.2022.9718847.

[10] Zhang, Mengmeng, Wei Li, and Qian Du. "Diverse region-based CNN for hyperspectral image classification." IEEE Transactions on Image Processing, 2018, Vol. 27(6), pages 2623-2634.https://doi.org/10.1109/TIP.2018.2809606.

[11] Jia, Xiao, Xiaolin Sun, and Xingang Zhang. "Breast cancer identification using machine learning." Mathematical Problems in Engineering, 2022 pages 1-8. https://doi.org/10.1155/2022/8122895.

[12] Wang, Xiaomei, Ijaz Ahmad, Danish Javeed, Syeda Armana Zaidi, Fahad M. Alotaibi, Mohamed E. Ghoneim, Yousef Ibrahim Daradkeh, Junaid Asghar, and Elsayed Tag Eldin. "Intelligent Hybrid Deep Learning Model for Breast Cancer Detection." Electronics, 2022, Vol. 11(17), pages 2767. https://doi.org/10.3390/electronics11172767.

[13] Sharma, Deepti, Rajneesh Kumar, and Anurag Jain. "Breast cancer prediction based on neural networks and extra tree classifier using feature ensemble learning." Measurement: Sensors, 2022, 24, pages 100560.https://doi.org/10.1016/j.measen.2022.100560.

[14] Raina, Rajat, Alexis Battle, Honglak Lee, Benjamin Packer, and Andrew Y. Ng. "Self-taught learning: transfer learning from unlabeled data." In Proceedings of the 24th international conference on Machine learning, 2007, pages 759-766. https://doi.org/10.1145/1273496.1273592.

[15] Abimannan, Satheesh, El-Sayed M. El-Alfy, Yue-Shan Chang, Shahid Hussain, Saurabh Shukla, and Dhivyadharsini Satheesh. "Ensemble Multifeatured Deep Learning Models and Applications: A Survey." IEEE Access, 2023, Vol. 11, pages 107194 - 107217 https://doi.org/10.1109/ACCESS.2023.3320042.

[16] Mikołajczyk, Agnieszka, and Michał Grochowski. "Data augmentation for improving deep learning in image classification problem." In 2018 international interdisciplinary PhD workshop (IIPhDW), IEEE, 2018, pages 117-122.https://doi.org/10.1109/IIPHDW.2018.8388338.

[17] Shen, Li, Laurie R. Margolies, Joseph H. Rothstein, Eugene Fluder, Russell McBride, and Weiva Sieh. "Deep learning to improve breast cancer detection on screening mammography." Scientific reports, 2019, Vol. 9(1), pages 12495.https://doi.org/10.1038/s41598-019-48995-4.

[18] Wang, Y., B. Acs, S. Robertson, B. Liu, Leslie Solorzano, Carolina Wählby, J. Hartman, and M. Rantalainen. "Improved breast cancer histological grading using deep learning." Annals of Oncology,2022, Vol. 33(1), pages 89-98.https://doi.org/10.1016/j.annonc.2021.09.007.

[19] Dewangan, Kranti Kumar, Deepak Kumar Dewangan, Satya Prakash Sahu, and Rekhram Janghel. "Breast cancer diagnosis in an early stage using novel deep learning with hybrid optimization technique." Multimedia Tools and Applications, 2022, Vol. 81(10), pages 13935-13960. https://doi.org/10.1007/s11042-022-12385-2.

[20] Sharma, Tripti, Rajit Nair, and S. Gomathi. "Breast cancer image classification using transfer learning and convolutional neural network." International Journal of Modern Research, 2022, Vol. 2(1), pages 8-16.

https://www.ijmore.co.in/article/view/5.html.

[21] Yu, Dianzhi, Jianwu Lin, Tengbao Cao, Yang Chen, Mingfei Li, and Xin Zhang. "SECS: An effective CNN joint construction strategy for breast cancer histopathological image classification." Journal of King Saud University-Computer and Information Sciences, 2023, Vol. 35(2), pages 810-820.https://doi.org/10.1016/j.jksuci.2023.01.017.

[22] Srikantamurthy, Mahati Munikoti, VP Subramanyam Rallabandi, Dawood Babu Dudekula, Sathishkumar Natarajan, and Junhyung Park. "Classification of benign and malignant subtypes of breast cancer histopathology imaging using hybrid CNN-LSTM based transfer learning." BMC Medical Imaging, 2023, Vol. 23(1), pages 19.https://doi.org/10.1186/s12880-023-00964-0.

[23] Patel, Vivek, Vijayshri Chaurasia, Rajesh Mahadeva, and Shashikant P. Patole. "GARL-Net: Graph Based Adaptive Regularized Learning Deep Network for Breast Cancer Classification." IEEE Access, 2023, Vol. 11, pages 9095-9112.https://doi.org/10.1109/ACCESS.2023.3239671.

[24] Saleh, Hager, Hashem Alyami, and Wael Alosaimi. "Predicting breast cancer based on optimized deep learning approach." Computational Intelligence and Neuroscience, 2022, Vol. 2022.https://doi.org/10.1155/2022/1820777.

[25] Sharma, Tripti, Rajit Nair, and S. Gomathi. "Breast cancer image classification using transfer learning and convolutional neural network." International Journal of Modern Research, 2022, Vol 2(1), pages 8-16.https://www.ijmore.co.in/article/view/5.html.

[26] Abdul Halim, Ahmad Ashraf, Allan Melvin Andrew, Mohd Najib Mohd Yasin, Mohd Amiruddin Abd Rahman, Muzammil Jusoh, Vijayasarveswari Veeraperumal, Hasliza A. Rahim, Usman Illahi, Muhammad Khalis Abdul Karim, and Edgar Scavino. "Existing and emerging breast cancer detection technologies and its challenges: a review." Applied Sciences, 2021, Vol. 11(22), pages 10753.https://doi.org/10.3390/app112210753.

[27] Zakareya, Salman, Habib Izadkhah, and Jaber Karimpour. "A New Deep-Learning-Based Model for Breast Cancer Diagnosis from Medical Images." Diagnostics, 2023, Vol. 13(11), pages 1944. https://doi.org/10.3390/diagnostics13111944.

[28] Koh, Jing Yu, Daniel Fried, and Ruslan Salakhutdinov. "Generating images with multimodal language models." arXiv preprint, 2023, arXiv:2305.17216. https://doi.org/10.48550/arXiv.2305.17216.

Authorized licensed use limited to: b-on: UNIVERSIDADE NOVA DE LISBOA. Downloaded on July 12,2025 at 22:05:21 UTC from IEEE Xplore. Restrictions apply.

[29] Naveed, Humza, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muhammad Usman, Nick Barnes, and Ajmal Mian. "A comprehensive overview of large language models." arXiv preprint 2023, arXiv:2307.06435. https://doi.org/10.48550/arXiv.2307.06435.

[30] Allugunti, Viswanatha Reddy. "Breast cancer detection based on thermographic images using machine learning and deep learning algorithms." International Journal of Engineering in Computer Science, 2022, Vol 4(1), pages 49-56.

[31] Nassif, Ali Bou, Manar Abu Talib, Qassim Nasir, Yaman Afadar, and Omar Elgendy. "Breast cancer detection using artificial intelligence techniques: A systematic literature review." Artificial Intelligence in Medicine, 2022, Vol. 127, pages 102276. https://doi.org/10.1016/j.artmed.2022.102276.

Authorized licensed use limited to: b-on: UNIVERSIDADE NOVA DE LISBOA. Downloaded on July 12,2025 at 22:05:21 UTC from IEEE Xplore. Restrictions apply.