Proceedings of Bhavisya Entrepreneur 2025: National Symposium on Entrepreneurship Innovation
ISBN: 978-93-343-9865-6

NSEI/2025/27

An Efficient Deep Neural Network Model for the Detection of Breast Cancer

Debjit Haldar[1], Debjit Makar [1], Chandramouli Haldar [2] , Suparna Biswas [1], Koushik Pal [1] , Anurima Majumder [6]

[1] Department of Electronics and Communication Engineering, GNIT, Kolkata

[2]Department of Computer Science Engineering , GNIT ,Kolkata

***Abstract*—** Breast cancer is one of the leading causes of mortality for women worldwide, and early detection significantly improves patient outcomes. One kind of deep learning technique that has shown remarkable results in automated medical image interpretation in recent years is Convolutional Neural Networks (CNN). This research proposes a CNN-based model for the accurate and efficient detection of breast cancer from histopathology and mammography images. The model automatically extracts hierarchical features from incoming pictures, eliminating the need for manual feature engineering. Using a publicly available benchmark dataset for training and validation, a number of performance metrics accuracy, sensitivity, specificity, and F1-score, were evaluated and achieved the maximum accuracy of 94%.

***Keywords*—** *Deep Learning, CNN, Breast Cancer, AI*

I. Introduction

In order to improve patient outcomes, breast cancer is still a major worldwide health concern that requires ongoing improvements in early detection techniques. An estimated 2.3 million new cases were detected in 2020 alone, accounting for 16% of cancer-related mortality in women and leading to almost 685,000 deaths year [1]. Because early diagnosis and treatments greatly improve prognosis and lessen illness burden, this widespread occurrence emphasizes how important they are [2]. Mammography and breast ultrasonography are the most common screening modalities utilized in early diagnosis [3].

These imaging methods are the main means of evaluating and identifying breast cancers, and ongoing advancements in their capabilities enable more precise diagnosis [4]. Beyond these traditional approaches, breast cancer diagnosis has been transformed by the combination of artificial intelligence and sophisticated image processing techniques, which have improved the performance of detecting minute abnormalities [5]. With an emphasis on the clinical value and limits of both established and new technologies, this review attempts to summarize the state of breast cancer detection techniques today. Additionally, it will examine how new non-invasive techniques, such liquid biopsies and biosensors, have the potential to revolutionize screening practices by providing more convenient and painless options for routine monitoring [6]. Furthermore, this review will delve into the challenges inherent in current diagnostic pathways, including issues of accessibility, cost, and the psychological impact on patients

ISBN: **978-93-343-9865-6**

[7,8]. This thorough analysis will evaluate the effectiveness, sensitivity, and specificity of different detection techniques critically, providing information on their relative benefits and the situations in which they are best used. Along with the revolutionary potential of nanotechnology and breath biopsies, the analysis will also cover developing technologies that have the potential to improve detection efficiency and lessen patient discomfort, such as enhanced mammography techniques and radionuclide approaches [8]. The technological foundations and clinical efficacy of well-known procedures like mammography, ultrasound, and magnetic resonance imaging as well as more recent developments like tomosynthesis, elastography, and molecular imaging will be closely examined in this review of the literature.

The paper is divided into a number of important sections. It starts with the Introduction, which gives background details, specifies the issue statement, lays out the goals, and highlights the work's contributions in addition to the paper's structure. The Literature Review comes next, providing a thorough summary of previous studies, pointing out any gaps, and demonstrating the necessity of the suggested investigation. The framework, methodology, algorithms, and models employed are then described in the Proposed Method section, which is accompanied when needed by diagrams or mathematical formulations. The experimental setup, performance evaluation metrics, and conclusions are described in the Results and Discussion section. The main results, contributions, drawbacks, and possible directions for future research are outlined in the Conclusion. The paper concludes with references.

II. Literature Review

This section provides a detailed exploration of the various methods employed in breast cancer detection, ranging from conventional imaging modalities to cutting-edge computational approaches. It specifically highlights the advanced image processing and artificial intelligence technologies in augmenting the accuracy and efficiency of early detection and diagnosis [9,10] of breast cancer. The subsequent subsections will delve into the intricacies of each detection method, evaluating their underlying principles, clinical applications, and inherent limitations. This structured approach ensures a thorough understanding of the current state of breast cancer detection, identifying areas for future research and technological development. The ongoing debate regarding the efficacy of breast cancer screening, particularly concerning mammography, will also be addressed (Breast Cancer Risk Assessment and Treatment Options with Radiation Therapy, a Review Study, n.d.). While mammography remains the gold standard for breast cancer screening, especially in women over 40, its limitations, such as reduced sensitivity in dense breast tissue and the risk of false positives, necessitate the exploration of supplementary and alternative detection methods[11,12]. For instance, dedicated computed tomography devices, including those utilizing cone-beam and phase-contrast technologies, offer full three-dimensional imaging capabilities and show promise in breast assessment [13]. Moreover, the integration of advanced imaging modalities like Magnetic Resonance Imaging and ultrasound further complements mammography, especially in cases of dense breast tissue, by offering superior soft-tissue contrast and multi-planar imaging capabilities for comprehensive assessment [14]. These advanced imaging techniques, in conjunction with traditional clinical examinations, significantly improve the diagnostic accuracy of breast cancer [15].

Furthermore, the advent of AI and ML has introduced a transformative paradigm in breast cancer detection by enabling automated image analysis, thereby enhancing diagnostic precision and

ISBN: **978-93-343-9865-6**

reducing inter-observer variability [10]. These computational approaches are particularly valuable in processing the vast amounts of data generated by modern imaging techniques, identifying subtle patterns that might escape human observation, and thereby leading to earlier and more accurate diagnoses [16]. Despite these technological advancements, the definitive diagnosis of breast cancer still primarily relies on pathological examination, which remains the gold standard for tissue characterization and tumor classification [14, 17]. However, the invasive nature of biopsy procedures underscores the ongoing need for improved non-invasive methods that can accurately assess breast cancer and reduce unnecessary biopsies. This underscores the imperative for continuous innovation in diagnostic methodologies, particularly those capable of providing high diagnostic accuracy with minimal patient discomfort [18]. Moreover, the identification of specific biomarkers, such as ERα isoforms and HER2 overexpression, through molecular diagnostic assessments further refines risk stratification and guides targeted therapeutic interventions (Breast Cancer Risk Assessment and Treatment Options with Radiation Therapy, a Review Study, n.d.). The ongoing advancements in imaging technologies, including multidetector computed tomography with dedicated protocols, further enhance the ability to characterize breast lesions and stage breast cancer, particularly in assessing multifocality and multicentricity [13]. This includes a higher number of suspicious axillary lymph nodes and better agreement with pathological findings for T-staging, although it is not recommended for screening due to higher radiation doses [13]. Future directions in breast cancer detection emphasize the integration of novel techniques, such as breath biopsies and X-ray diffraction of hair, which offer potential for earlier, non-invasive, and more patient-friendly diagnostic tools [19]. Additionally, the integration of artificial intelligence(AI) and machine learning(ML) algorithms is poised to further revolutionize diagnostic accuracy by identifying subtle patterns in complex imaging data, thereby facilitating earlier and more precise detection of malignant transformations [20].

The continued development of these integrated approaches promises to significantly increase patient outcomes by adding earlier interventions and more personalized treatment strategies [21]. The urgency for highly sensitive and rapid diagnostic methods for early-stage breast cancer, particularly those addressing the limitations of existing techniques like cost and time, continues to drive innovation in biosensor development for biomarker detection [22]. Magnetic resonance imaging is a valuable tool for assessing breast cancer size, location, and detecting additional abnormal tissues, particularly beneficial for women with genetic predisposition or elevated breast density (Breast Cancer Risk Assessment and Treatment Options with Radiation Therapy, a Review Study, n.d.). Complementing these imaging modalities, the application of ML techniques in diagnostic medicine is increasingly recognized for its efficiency in detecting and intervening in breast cancer[23]. Despite the advancements, challenges persist, including the high cost and limited availability of certain advanced imaging techniques like MRI, necessitating continued research into more accessible and equally efficacious diagnostic tools [13]. Furthermore, while technological innovations have significantly advanced breast cancer care, ethical, social, and practical implications must be carefully considered and managed to ensure equitable access and optimal patient outcomes[24]. Artificial intelligence, with its ability to analyze extensive medical datasets and identify subtle patterns, holds significant promise for enhancing early detection and personalizing treatment strategies by predicting efficacy and recommending tailored medications [25].

ISBN: **978-93-343-9865-6**

Regenerative AI, in particular, is transforming breast cancer diagnosis and treatment through image analysis[26]. Moreover, generative AI models are accelerating drug discovery by rapidly designing and screening novel molecules targeting breast cancer pathways, while AI-powered remote monitoring tools provide real-time guide patient care [26] system.

II . Proposed Method

The goal of the suggested approach is to use clinical or image-based datasets to create an effective deep learning model for the precise identification of breast cancer. The architecture uses dropout regularization and dense (completely linked) layers to increase classification performance and decrease overfitting. Here are the essential steps:

A. Data Collection and Preprocessing:

In this work we have used Wisconsin Breast Cancer Dataset of breast cancer. This dataset consists of 569 samples and 30 features and two classes benign (B) or malignant (M). Missing values are handled and categorical data is encoded if required. Feature scaling is used to standardize the input data to a range between 0 and 1 for stable network training. Training uses 80% of the dataset, validation uses 20%.

B. Deep Neural Network Architecture:

The proposed DNN consists of three dense layers and two dropout layers to prevent overfitting. The input layer takes in the breast cancer dataset's pre-processed features. Dense layer with 64 neurons and ReLU activation function is known as Hidden Layer 1. To enhance generalization, 30% of neurons are randomly deactivated using the Dropout Layer (rate = 0.3). The second hidden layer is a dense layer that uses ReLU activation and has 32 neurons. Dropout Layer for extra regularization (rate = 0.2).
The third hidden layer is a dense layer that uses ReLU activation and has 16 neurons.
Output Layer: One neuron in a dense layer (classified as either benign or malignant). Using sigmoid activation, probabilities ranging from 0 to 1 are produced.

C. Model Training:

To calculate the error between the expected and real labels, Binary Cross-Entropy is utilized. Effective convergence is achieved by utilizing the Adam optimizer, also known as adaptive moment estimation. The model is trained over 100 epochs with a batch size of 32. Early Stopping is used to avoid overfitting by stopping training when validation loss no longer improves. Model Summary is also shown in Fig.1

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	1,984
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2,080
dropout_1 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 16)	528
dense_3 (Dense)	(None, 1)	17

Fig. 1. Model Summary for the detection of Breast Cancer

ISBN: **978-93-343-9865-6**

III. EXPERIMENTAL RESULTS

Various performance metrics, including accuracy, precision, recall, confusion matrix, accuracy curve, and loss curve, were used to assess the experimental outcomes of the suggested approach. By calculating the percentage of correctly identified cases across all samples, accuracy indicates the model's overall correctness. Precision and memory are also taken into account because accuracy alone may be deceptive in medical applications such as breast cancer screening. While recall (also known as sensitivity) gauges the model's capacity to accurately identify all actual positive cases, decreasing false negatives, precision shows the proportion of samples that are predicted to be positive that are actually positive, lowering the likelihood of false positives. Different metrics are mentioned in Fig.2.

	precision	recall	f1-score	support
malignant	0.91	0.94	0.92	32
benign	0.96	0.94	0.95	54
accuracy			0.94	86
macro avg	0.94	0.94	0.94	86
weighted avg	0.94	0.94	0.94	86

Fig. 2. Different metrics of the proposed model

The model's learning behavior is also observed and overfitting or underfitting is detected using the accuracy curve as shown in Fig.3, which depicts training and validation accuracy over epochs. In a similar vein, the loss curve illustrates how training and validation loss fluctuate over time; a continuously declining trend suggests successful learning, whereas a divergence between training and validation loss suggests overfitting as shown in Fig.4. When combined, these metrics and visuals offer a thorough assessment of the model's functionality and deendability in real-world scenarios.

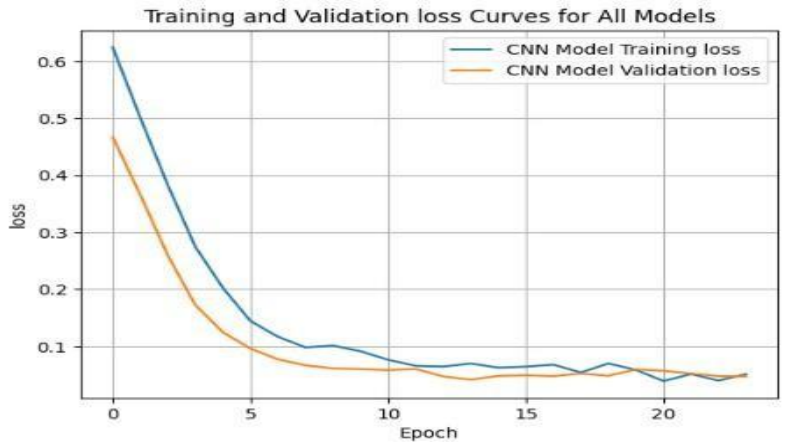


Fig. 3. Training and validation loss curve for the proposed model

ISBN: **978-93-343-9865-6**

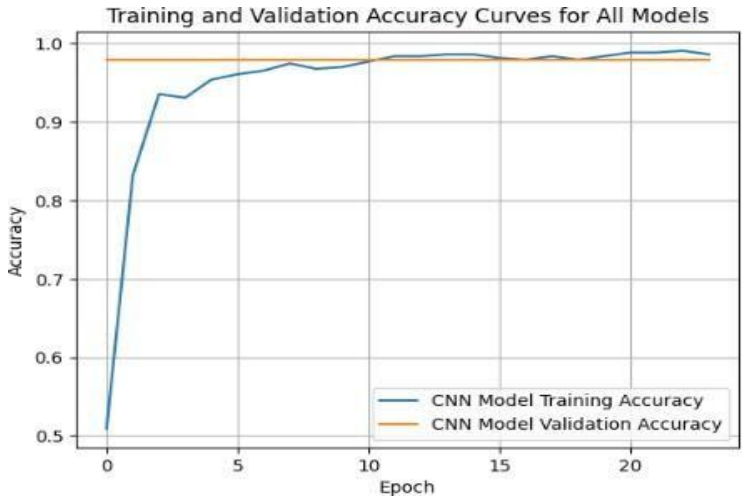


Fig. 4. Training and validation accuracy curve for the proposed model

IV. CONCLUSION AND FUTURE SCOPE

To aid in early and precise diagnosis, a deep learning-based method for breast cancer detection was put forth and assessed in this work. By successfully learning discriminative features from medical imaging data and attaining high accuracy, precision, and recall—all essential for a trustworthy medical diagnosis—the model showed encouraging performance. The proposed model provides the accuracy of 94%.

The suggested approach can be expanded in the future by adding bigger and more varied datasets to strengthen its capacity to generalize across various imaging modalities and demographics. It may be possible to integrate explainable AI (XAI) approaches to make decision-making more transparent and aid clinicians in comprehending the logic behind forecasts. Lastly, a more thorough and accurate breast cancer diagnosis system may result from integrating deep learning with additional methods like multimodal imaging or genomics data analy

References

[1] Aboagye, S. O., Hunt, J., Ball, G., & Wei, Y. (2024). Portable noninvasive technologies for early breast cancer detection: A systematic review [Review of Portable noninvasive technologies for early breast cancer detection: A systematic review]. Computers in Biology and Medicine, 182, 109219. Elsevier BV. https://doi.org/10.1016/j.compbiomed.2024.109219

[2] Luo, L., Wang, X., Lin, Y., Ma, X., Tan, A., Chan, R., Vardhanabhuti, V., Chu, C. W., Cheng, K., & Chen, H. (2024). Deep Learning in Breast Cancer Imaging: A Decade of Progress and Future Directions [Review of Deep Learning in Breast Cancer Imaging: A Decade of Progress and Future

ISBN: **978-93-343-9865-6**

Directions]. IEEE Reviews in Biomedical Engineering, 1. Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/rbme.2024.3357877

[3] Chen, J., Pan, T., Zhu, Z., Liu, L., Zhao, N., Xue, F., Zhang, W., Wu, Y., Cai, C., Luo, X., Lin, B., Wang, X., Ye, Q., Gao, R., Zhou, Z., Beatson, R., Tang, J., Ming, R., Wang, D., … Zhou, G. (2025). A deep learning-based multimodal medical imaging model for breast cancer screening. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-99535-2

[4] Gerami, R., Joni, S. S., Akhondi, N., Etemadi, A., Fosouli, M., Eghbal, A. F., & Souri, Z. (2022). A literature review on the imaging methods for breast cancer. [Review of A literature review on the imaging methods for breast cancer.]. PubMed, 14(3), 171. National Institutes of Health. https://pubmed.ncbi.nlm.nih.gov/35891932

[5] Zhu, Z., Sun, Y., & Asli, B. H. S. (2024). Early Breast Cancer Detection Using Artificial Intelligence Techniques Based on Advanced Image Processing Tools. Electronics, 13(17), 3575. https://doi.org/10.3390/electronics13173575

[6] Grasso, A., Altomare, V., Fiorini, G., Zompanti, A., Pennazza, G., & Santonico, M. (2025). Innovative Methodologies for the Early Detection of Breast Cancer: A Review Categorized by Target Biological Samples [Review of Innovative Methodologies for the Early Detection of Breast Cancer: A Review Categorized by Target Biological Samples]. Biosensors, 15(4), 257. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/bios15040257

[7] Halim, A. A. A., Andrew, A. M., Yasin, M. N. M., Rahman, M. A. A., Jusoh, M., Veeraperumal, V., Rahim, H. A., Illahi, U., Karim, M. K. A., & Scavino, E. (2021). Existing and Emerging Breast Cancer Detection Technologies and Its Challenges: A Review [Review of Existing and Emerging Breast Cancer Detection Technologies and Its Challenges: A Review]. Applied Sciences, 11(22), 10753. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/app112210753

[8] Mishra, J., Kumar, B., Targhotra, M., & Sahoo, P. (2020). Advanced and futuristic approaches for breast cancer diagnosis. Future Journal of Pharmaceutical Sciences, 6(1). https://doi.org/10.1186/s43094-020-00113-2

[9] Zhu, Z., Sun, Y., & Asli, B. H. S. (2024). Early Breast Cancer Detection Using Artificial Intelligence Techniques Based on Advanced Image Processing Tools. Electronics, 13(17), 3575. https://doi.org/10.3390/electronics13173575

ISBN: **978-93-343-9865-6**

[10] Rentiya, Z., Mandal, S., Inban, P., Vempalli, H., Dabbara, R., Ali, S., Kaur, K., Adegbite, A., Intsiful, T. A., Jayan, M., Odoma, V. A., & Khan, A. (2024). Revolutionizing Breast Cancer Detection With Artificial Intelligence (AI) in Radiology and Radiation Oncology: A Systematic Review [Review of Revolutionizing Breast Cancer Detection With Artificial Intelligence (AI) in Radiology and Radiation Oncology: A Systematic Review]. Cureus. Cureus, Inc. https://doi.org/10.7759/cureus.57619

[11] Ugwah, J., O'Sullivan, M. J., O'Donnell, B. D., & Moore, E. (2021). Recent Advances in Development of New Technology in Pre and Intra Operative Breast Cancer Diagnoses. Journal of Cancer Treatment and Diagnosis, 5(2), 1. https://doi.org/10.29245/2578-2967/2021/2.1192

[12] Khalid, A., Mehmood, A., Alabrah, A., Alkhamees, B. F., Amin, F., AlSalman, H., & Choi, G. S. (2023). Breast Cancer Detection and Prevention Using Machine Learning. Diagnostics, 13(19), 3113. https://doi.org/10.3390/diagnostics13193113

[13] 13. Felipe, V. C., Graziano, L., Barbosa, P. N. V. P., Calsavara, V. F., & Bitencourt, A. G. V. (2020). Multidetector Computed Tomography with Dedicated Protocol for Breast Cancer Locoregional Staging: Feasibility Study. Diagnostics, 10(7), 479. https://doi.org/10.3390/diagnostics10070479

[14] Fernandez, E., Castillo-Araníbar, P., Castillo, E., Oller, B., Ventura-Zaa, L., Eguiluz-Rodriguez, G., González-Posadas, V., & Segovia-Vargas, D. (2024). Dielectric Characterization of Ex-Vivo Breast Tissues: Differentiation of Tumor Types through Permittivity Measurements. Cancers, 16(4), 793. https://doi.org/10.3390/cancers16040793

[15] Arshad, M., Shahriar, S., & Anjum, K. (2023). The Power Of Simplicity: Why Simple Linear Models Outperform Complex Machine Learning Techniques -- Case Of Breast Cancer Diagnosis. arXiv (Cornell University). https://doi.org/10.48550/arXiv.2306.02449

[16] Wang, L. (2024). Mammography with deep learning for breast cancer detection. Frontiers in Oncology, 14. https://doi.org/10.3389/fonc.2024.1281922

[17] He, J., Liu, N., & Zhao, L. (2025). New progress in imaging diagnosis and immunotherapy of breast cancer [Review of New progress in imaging diagnosis and immunotherapy of breast cancer]. Frontiers in Immunology, 16. Frontiers Media. https://doi.org/10.3389/fimmu.2025.1560257

[18] Drukteinis, J. S., Mooney, B., Flowers, C. I., & Gatenby, R. A. (2013). Beyond Mammography: New Frontiers in Breast Cancer Screening [Review of Beyond Mammography: New Frontiers in

ISBN: **978-93-343-9865-6**

Breast Cancer Screening]. The American Journal of Medicine, 126(6), 472. Elsevier BV. https://doi.org/10.1016/j.amjmed.2012.11.025

[19] Mishra, J., Kumar, B., Targhotra, M., & Sahoo, P. (2020). Advanced and futuristic approaches for breast cancer diagnosis. Future Journal of Pharmaceutical Sciences, 6(1). https://doi.org/10.1186/s43094-020-00113-2

[20] Vrdoljak, J., Krešo, A., Kumrić, M., Martinović, D., Cvitković, I., Grahovac, M., Vickov, J., Bukić, J., & Božić, J. (2023). The Role of AI in Breast Cancer Lymph Node Classification: A Comprehensive Review [Review of The Role of AI in Breast Cancer Lymph Node Classification: A Comprehensive Review]. Cancers, 15(8), 2400. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/cancers15082400

[21] Ahn, J. S., Shin, S., Yang, S., Park, E. K., Kim, K. H., Cho, S. I., Ock, C., & Kim, S. (2023). Artificial Intelligence in Breast Cancer Diagnosis and Personalized Medicine [Review of Artificial Intelligence in Breast Cancer Diagnosis and Personalized Medicine]. Journal of Breast Cancer, 26(5), 405. https://doi.org/10.4048/jbc.2023.26.e45

[22] Wang, L. (2017). Early Diagnosis of Breast Cancer [Review of Early Diagnosis of Breast Cancer]. Sensors, 17(7), 1572. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/s17071572