

Deep Neural Network Powered System for Precision Breast Cancer Analysis and Stage Classification

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Abstract:

The global rise in breast cancer cases has made early diagnosis more important than ever, highlighting the need for fast and dependable detection methods. This study presents a refined Deep Neural Network (DNN) approach intended at taming the identification and classification of breast cancer. The model uses modern machine learning methods to boost both accurateness and efficiency in diagnostic processes. The work provides a detailed look at how DNNs can support breast cancer detection by analyzing the complex visual patterns found in mammogram images. The proposed network architecture is built with multiple layers, each responsible for learning different levels of image features. Convolutional layers extract small, localized patterns, while fully connected layers interpret broader, high-level structures. Together, they enable the model to detect subtle indicators that may signal the presence of tumors. To ensure strong performance across various types of breast tissue and lesion appearances, the network is trained using a variety of datasets. Transfer learning is also incorporated to reduce the difficulties related to limited labeled medical data. By using knowledge from models previously trained on large image collections, the system becomes more adaptable and effective. The model's presentation is assessed using extensively recognized benchmark datasets and associated with both old techniques and recent deep learning approaches. All overall accuracy and the confusion matrix demonstrate that the proposed DNN achieves high diagnostic reliability. These results propose that the model offers a capable solution for early breast cancer finding and could support more accurate and efficient clinical decision-making.

Keywords: Deep Neural Network (DNN), Threshold based segmentation, CLAHE (Contrast Limited Adaptive Histogram Equalization) image Enhancement, Breast cancer prediction and classification,

1. Introduction

Breast cancer has become increasingly common worldwide and remains a condition that can profoundly affect the lives of those diagnosed. Because of this, early detection plays a crucial role in taming treatment success and long-term survival. Recent advancements in deep learning—a powerful area within machine learning—are reshaping how breast cancer can be identified and analyzed. Deep learning models are inspired by how the human brain processes information, using interconnected neural networks capable of learning complex relationships from large datasets.

When applied to breast cancer diagnosis, these models are trained on extensive collections of medical images, including mammograms, ultrasound scans, and MRI studies. This training enables them to analyze subtle visual cues and patterns that may be difficult for the human eye to detect. Their ability to recognize fine-grained abnormalities makes deep learning systems highly promising tools for enhancing detection accuracy. One of the most notable strengths of deep learning in medical imaging is its capacity for continuous improvement. As the model encounters more data and a broader range of clinical scenarios, its ability to differentiate between harmless and potentially harmful features becomes increasingly refined. This ongoing learning process leads to greater diagnostic precision over time.

Machine learning systems also offer the advantage of speeding up the diagnostic workflow. Automated image interpretation can support clinicians by providing fast, consistent assessments, easing the burden of manual review and enabling quicker intervention when abnormalities are detected. Despite these advances, several challenges remain in the widespread use of deep learning for cancer detection. Issues such as rigorous model validation, ethical considerations, and the need for seamless integration into existing clinical routines must be addressed. Researchers and medical

professionals continue to explore how these technologies can be safely and effectively implemented to support global efforts in reducing breast cancer mortality.

Deep Neural Networks (DNNs), in particular, have become a powerful approach for analyzing mammographic images, which are a cornerstone of routine breast cancer screening. Mammograms generate detailed X-ray images of breast tissue, and DNNs are especially well-suited to interpreting these complex visuals.

By learning from large image datasets, DNNs develop the ability to identify subtle characteristics associated with both cancerous and non-cancerous conditions. Their strength lies in their capability to automatically discover relevant features without relying on manually crafted rules. This allows DNNs to detect intricate patterns that traditional image processing methods may overlook. With continued exposure to diverse imaging examples, these networks grow more adept at recognizing early signs of tumors and other abnormalities. Using DNNs for breast cancer detection can lead to faster and more reliable mammogram analysis. Automated systems can assist radiologists by highlighting suspicious regions, helping reduce missed detections and lowering the likelihood of unnecessary follow-ups caused by false alarms. Ultimately, the goal is to improve patient outcomes by supporting more timely and accurate diagnostic decisions.

However, introducing DNN-based tools into clinical settings must be approached carefully. Ensuring proper validation, transparency, and thoughtful consideration of ethical concerns is essential to maintain trust and reliability. As research progresses, DNNs are expected to play a significant role in advancing breast cancer screening methods and contributing to global initiatives aimed at reducing the impact of this disease.

2. Literature Review

In 2020, more than two million new cases were recorded worldwide, and approximately 685,000 individuals lost their lives to the disease. These numbers highlight the global burden of breast cancer and reaffirm its status as the most commonly diagnosed cancer among women. The urgent need for timely and precise detection is clear, as early diagnosis can significantly improve patient outcomes and raise survival rates to nearly 50%. In this context, deep learning-based Computer-Aided Detection (CAD) systems have emerged as a transformative development in medical imaging, particularly in breast cancer screening. These technologies have greatly enhanced early-stage identification, ultimately contributing to better treatment results. This review provides a detailed examination of various deep learning models developed for breast cancer detection.

Breast cancer remains the leading malignant disease affecting women across the globe [1]. Furthermore, the number of new cases rise by nearly 70% in the next two decades. Among major cancers—such as lung, liver, stomach cancers and colon—breast cancer ranks as the fifth-deadliest illness [2]. In comparison, Male Breast Cancer (MBC) remains extremely uncommon, and current treatment strategies are largely based on techniques originally developed for FBC, despite the biological differences between the two diseases [3]. Additionally, gaps in public knowledge about breast cancer have turned FBC into a rapidly growing health concern in several South Asian countries. This lack of awareness underscores the necessity for focused research and education initiatives tailored to the needs of diverse populations.

In countries such as Bangladesh, breast cancer (BrC) often remains undetected until it has progressed to advanced stages [4–6]. This situation highlights the urgent need for a healthcare system that is both affordable and accessible, enabling timely diagnosis for women across various socio-economic groups. Presently, late-stage breast cancer in these settings has a survival rate of only 30%. Establishing cost-effective screening strategies is therefore essential to raise survival rates to approximately 50% through earlier detection [1].

Accurate diagnosis relies heavily on identifying the correct stages of cancer and classifying it precisely. Imaging techniques represent a cornerstone of this diagnostic process, often outperforming other methods. These imaging tools include histopathology (Hp) slides, mammography, ultrasound imaging, and MRI [7,8]. Each modality contributes unique insights into the nature and progression of the disease.

A precise diagnosis requires the expertise of trained pathologists, whose knowledge ensures accurate interpretation of imaging results and helps guide appropriate treatment decisions. Strengthening the healthcare workforce—especially in resource-limited regions—is thus a crucial step to-

ward improving breast cancer outcomes. Misdiagnosis, particularly at early stages, remains a significant challenge. It have been developed to support clinicians by analyzing mammograms and identifying abnormalities [9]. These tools offer fast, reliable, and inexpensive diagnostic assistance, contributing to more than a 20% improvement in detection accuracy over the last decade [10].

DL based CAD frameworks have achieved remarkable progress across numerous medical specialties, including radiology, cardiology, pathology, pharmacology, oncology, and genomics, enabling more accurate diagnosis and prognosis of diseases [11–19]. In breast cancer imaging, DL methods demonstrate exceptional performance across mammography, ultrasound, and digital breast tomosynthesis (DBT) for cancer identification [20,21]. Due to their superior accuracy, deep learning-driven diagnostic models have become a central focus in breast cancer research, with numerous recent publications validating their effectiveness [22–24].

As deep learning continues to refine automated diagnostic capabilities, these algorithms have become essential in addressing the limitations of traditional methods. While several review papers discuss different classification strategies, only a few have provided clear direction for future investigations. Many earlier studies centered on conventional Artificial Neural Networks (ANNs) or traditional machine learning approaches, often overlooking newer architectures such as Extreme Learning Machines (ELMs) and Generative Adversarial Networks (GANs) [25,26].

Furthermore, emerging imaging techniques including infrared thermal imaging, computed tomography and digital breast tomosynthesis, have been introduced in recent breast cancer research but remain largely unaddressed in prior review literature. This study aims to fill these gaps by offering a systematic and analytical assessment of deep-learning-based image classification approaches within CAD systems. The review covers six core areas: diagnostic model structures, datasets and preprocessing methods, breast cancer imaging techniques, evaluation metrics, and future research opportunities. By addressing shortcomings in earlier reviews, this study makes a significant contribution to ongoing advancements in deep learning-assisted breast cancer diagnosis.

3. Methodology Used

The proposed architecture diagram using Deep Neural Network (DNN) based breast cancer detection system illustrates the major stages involved in the workflow. The system begins with mammogram images supplied as input. These images first undergo preprocessing, which includes operations such as cropping, binarization, and CLAHE to improve clarity and enhance important visual features. Following this, the processing stage carries out both segmentation and tumor identification. A threshold-based segmentation method is useful to separate the suspected cancer region from the enhanced image. The segmented output is then passed to the DNN classifier, which determines the presence of a tumor and categorizes it into the appropriate stage. The complete function of the proposed method is shown in Figure 1.

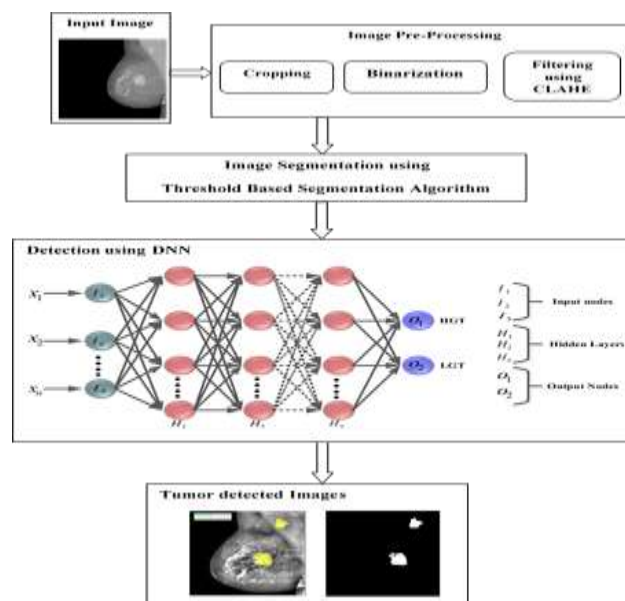


Figure 1: Architecture Diagram

a) Image Pre-Processing:

(i) Cropping: Image cropping refers to the process of selecting a desired region of interest (ROI) from an image and removing the surrounding areas that are not needed.

Step 1: Selecting Crop Region

Specify the size or exact location of the area want to retain in image. This can be defined either by using precise pixel values or by expressing the region as a percentage of the image's dimensions.

Step 2: Image Size

Identify the original image's dimensions, including its height and width.

Step 3: Crop Box

Generate a rectangular area that specifies portion of the image you want to retain. This region is typically defined using the coordinates of its top-left and bottom-right corners.

Step 4: Check Bounds

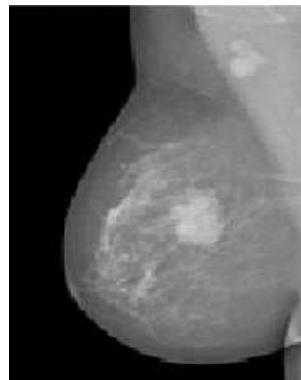
Verify that coordinates of the cropping region fall within the limits of the original image. If any part of the defined box extends outside the image, modify the coordinates accordingly to keep the crop area completely inside the image boundaries.

Step 5: Crop Operation

Retrieve all pixel values contained inside the specified cropping rectangle to produce the final cropped image. This is done by accessing or looping through the pixels that fall within the defined region.



(a) Mammogram Image



(b) Region of Interest Image

Figure 2 a and 2 b show input image and Region of Interest image respectively

(ii) Binarization: Binarization is a technique used to transform a grayscale image into a binary image, where every pixel is represented as either black or white. This is typically done by applying a thresholding method, which compares each pixel's intensity to a chosen threshold value and assigns it to one of the two classes accordingly.

Step 1: Gray scale Conversion:

If the image is in color, convert it to grayscale.

Step 2: Histogram Computation:

Compute the histogram of pixel intensities in the grayscale image. The histogram represents the distribution of pixel values.

Step 3: Choose Threshold:

Select a threshold value to separate foreground and background using OTSU algorithm

Step 4: Apply Threshold:

Assign a pixel value of 0 (black) to all pixels equal to or above the threshold.

$$B(x, y) = \begin{cases} 0 & \text{if } (I(x, y) < T) \\ 255 & \text{if } (I(x, y) \geq T) \end{cases} \quad [1]$$

Where:

$B(x, y)$ - Binary representation for the pixel

$I(x, y)$ - brightness of the associated

T - as the chosen threshold amount



Figure 3 Binarized image

Figure 3 shows the binary image for the cropped image.

(iii) Image Enhancement using CLAHE:

It involves several mathematical steps.

Let's define some terms:

Step 1: Divide the Image into Tiles

Let T_i represent the set of pixels within the i^{th} tile.

Step 2: Compute Histograms for Each Tile

$$Hi(z) = \sum_{(x,y) \in T_i} \delta(I(x, y) - z) \quad [2]$$

Where δ is the Dirac delta function.

Step 3: Redistribute Clipped Pixels

$$R_i(z) = \frac{\sum_{z1 > \text{Cliplimit}} H_i(Z1) - \text{Cliplimit}}{\text{Number of Pixels in } T_i} \quad [3]$$

Step 4: Interpolation

$$B(x, y) = I(x, y) + R_i(I(x, y)) \quad [4]$$

Image (left) and Contrast Enhanced Image

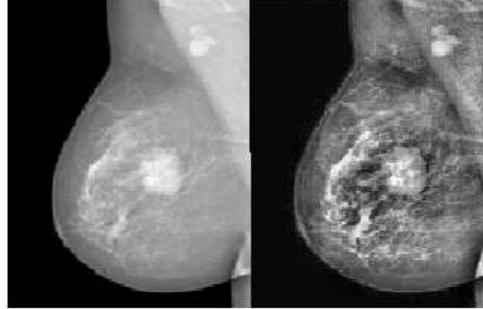


Figure 4-Cropped Image and CLAHE Image

Figure 4 shows the cropped image and CLAHE enhanced image.

b) Threshold based Segmentation Algorithm

Below is a step-by-step explanation of a generic threshold-based segmentation algorithm:

Step 1: Create a Binary mask

Initialize an empty binary mask $M(x, y)$ of the same size input image. The mask will be used to classify pixels into different regions.

Step 2: Segmentation

For each pixel in an image:

$$G(x, y) = \begin{cases} 1 & \text{if } I(x, y) \geq T \\ 0 & \text{if } I(x, y) < T \end{cases} \quad [5]$$

The pixel is assigned to the foreground (region of interest) if its intensity is greater than or equal to the threshold, otherwise, it is assigned to the background.

Step 3: Output

The binary mask $M(x, y)$ represents the segmented regions of the input image.

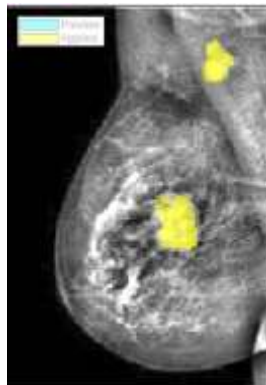


Figure 5: Segmented Image

Figure 5 shows the segmented image threshold-based segmentation algorithm.

c) Detection and classification of Tumor using DNN algorithm

Classification of tumors using a DNN algorithm:

Step 1: Neural Network Model

- Define a neural network architecture for tumor detection and classification.
- Let $F(X_{\text{preprocessed}}; \Theta)$ be the output of the neural network,
Where
 Θ represents the set of parameters learning..

Step 2: Training

- Use a labeled dataset $D = \{(X_i, Y_i)\}$ where X_i is an input image and Y_i is the corresponding tumor
- Define a loss function L .
- Update the parameters Θ using optimization

Step 3: Post-processing

Apply post-processing steps if needed, such as filtering out small detections or refining the tumor boundaries.



Figure 6: Tumor detected Image

Figure 6 shows the tumor detected in the segmented image.

4. Dataset

The CBIS-DDSM dataset is an improved and standardized extension of the original Digital Database for Screening Mammography (DDSM). The DDSM collection contains 2,620 film-based mammography studies, totaling 10,239 images, and includes a comprehensive range of normal, benign, and malignant cases. Each case is paired with confirmed pathology information, making the dataset a highly valuable resource for developing and evaluating computer-aided decision-support systems in breast cancer imaging. Its large scale and carefully validated ground truth have made DDSM one of the foundational datasets in this field.

The CBIS-DDSM subset undergoes an additional refinement process. Selected under the guidance of an expert mammographer, it is designed to preserve the core strengths of the DDSM while providing improvements in quality, consistency, and clinical relevance. This curated version aligns more closely with modern research requirements and the increasing precision needed in contemporary breast imaging applications.

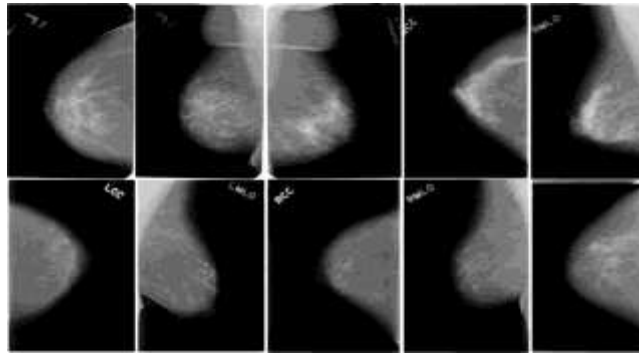


Figure 7: Dataset CBIS-DDSM

The dataset used in this study is accessible through the following link: <https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset>. Figure 7 presents sample images taken directly from this dataset to illustrate the types of mammographic cases included.

5. Results and Discussion

The proposed work used MATLAB 2023a with the dataset CBIS-DDSM. Table 1 shows the number of images used for training, validation and testing.

Table 1: Dataset for Training, Validation and Testing

Total No. of images	Training (80%)	Validation (10%)	Testing (10%)
10239	8191	1024	1024

a) Accuracy Analysis

The accuracy achieved by the artificial intelligence model for breast cancer detection is summarized in Table 2, while the performance of each machine learning classifier is illustrated in Figure 8. According to the results, the accuracy values for SVM, KNN, DT, LDA, RF, and the proposed DNN model are 65%, 62.3%, 71.5%, 88.90%, 74.90%, and 91.8%, respectively. These comparisons indicate that the proposed DNN architecture outperforms all other classifiers, demonstrating the highest level of accuracy. This confirms that the DNN model is the most effective and reliable approach for breast cancer detection among the methods evaluated.

Table 2: Accuracy of various ML methods [27] [28]

Sl.No	Algorithms	Accuracy in %
1	SVM	65.0
2	LDA	62.3
3	KNN	71.5
4	Decision Tree	88.9
5	Random Forest	74.9
6	Proposed work - DNN	91.8

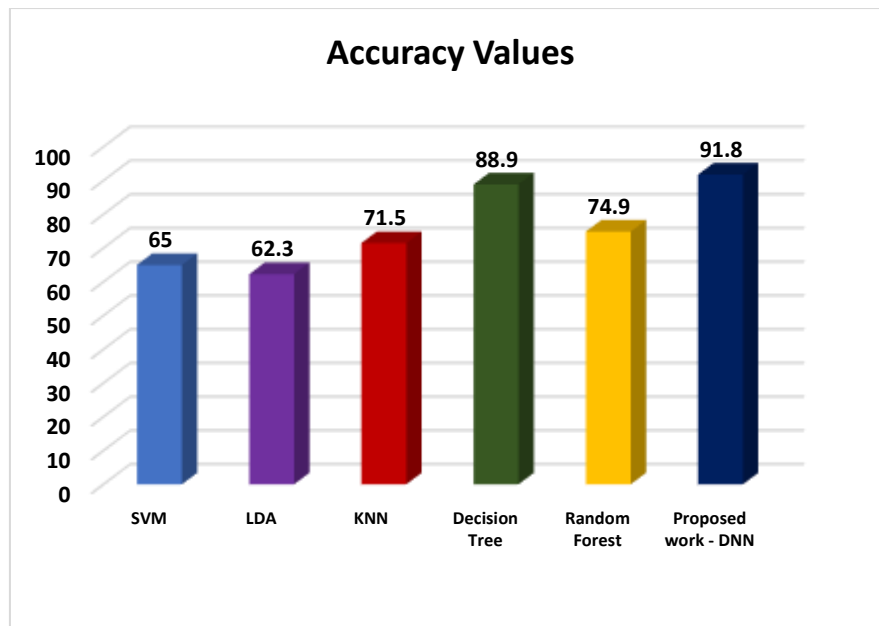


Figure 8: Accuracy of different classifiers

The literature review indicates that a substantial amount of breast cancer diagnosis research has relied on mammographic images. As mammograms continue to increase in complexity, the need for an effective and robust feature extraction technique becomes evident. In response, this study introduces a hybrid feature extraction approach designed to capture the most relevant characteristics necessary for accurate breast cancer identification. Based on the results obtained, the proposed method demonstrates strong suitability for detecting breast cancer using mammographic imaging.

b) Classification Analysis

The benchmark used for breast cancer classification in this study follows the updated guidelines available at the link: <https://www.jbcp.jo/understandingbreastcancer/33>. Following these criteria, the proposed method categorizes tumors into five stages—Stage 0, Stage 1, Stage 2, Stage 3, and Stage 4—based on tumor size. Table 3 presents the benchmark values for breast cancer stage classification, which are used to evaluate and compare the effectiveness of the proposed approach.

Table 3: Benchmark for breast cancer stage classification

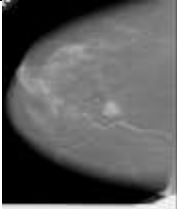
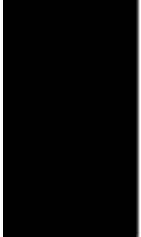
SL.No	Size	Stage
1	No Cancer	Stage 0
2	Less than 2 cm	Stage 1
3	2 – 5 cm	Stage 2
4	5 cm and larger	Stage 3
5	Any size	Stage 4

A selection of sample images from the dataset was used to analyze and classify tumors across the different stages. Table 4 outlines the staging process by determining the tumor size, which is calculated from the physical dimensions derived using pixel intensity values and the total number of pixels corresponding to the tumor region.

$$\text{Physical Size} = \frac{\text{Pixel Size}}{\text{Resolution}}$$

[6]

Table 4: Classification Analysis

S.No	Original Image	Detected Image	Size of the Tumor	Stage identified.
1.			Tumor 1 -2 cm Tumor 2- 1.1 cm	STAGE 2
2.			Tumor 1-1.3 cm	STAGE 1
3.			Tumor 1-1.7 cm	STAGE 1
4.			No tumor identified	STAGE 0
5.			Tumor 1- 5.3 cm Tumor 2- 2.8 cm	STAGE 3

c) Confusion Matrix:

A confusion matrix analysis was conducted on the DNN classifier to provide a deeper understanding of its performance. The results indicate that the DNN model correctly predicted most samples across all five stages. Stage 0 exhibited the highest classification accuracy, making it the easiest stage for the model to identify. In contrast, malignant categories presented the greatest classification challenges. The most frequent misclassification within malignant calcifications occurred when samples were labeled as Stage 2, followed by Stage 3. Similarly, Stage 2 samples were most often misclassified as Stage 4, and in some cases as Stage 5. Figure 9 illustrates the confusion matrix, offering a detailed breakdown of the DNN-based five-stage tumor classification results.

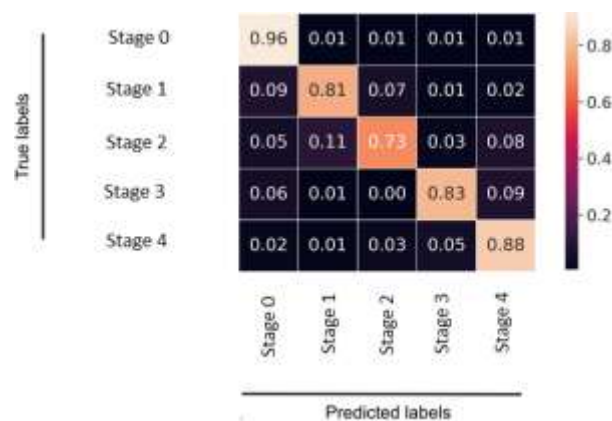


Figure 9: Confusion matrix analysis of 5-Stage Tumor classification for DNN

6. Conclusion

The breast cancer prediction and classification model, which integrates a DNN-based machine learning framework with threshold-driven segmentation, achieved a notable accuracy of 91.8%. This high performance reflects the model's strong capability to differentiate among various stages of breast cancer. The use of a Deep Neural Network enables the system to automatically learn complex features and subtle patterns within the data, making it highly effective for the detailed task of multi-stage classification. Incorporating threshold-based segmentation as a preprocessing technique further enhances the model by isolating the most relevant regions of interest, thereby improving overall accuracy. The combined use of DNN architecture and segmentation methods demonstrates significant potential for advancing medical image analysis. With its focus on precise classification and stage-specific identification, the model represents a meaningful advancement in breast cancer diagnostics. This approach not only strengthens early detection efforts but also supports more personalized treatment planning for patients at different stages of the disease. Continued research and refinement of this methodology can lead to an even more robust and clinically valuable tool, improving diagnostic confidence and contributing to better outcomes in breast cancer care.

Conflict of Interest: There is no conflict of Interest..

Data Availability: Dataset available in the following link, <https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset>

REFERENCES

1. Breast Cancer. 2021. Available online: <https://www.who.int/news-room/fact-sheets/detail/breast-cancer> (accessed on 19 July 2021).
2. Sung, H.; Ferlay, J.; Siegel, R.L.; Laversanne, M.; Soerjomataram, I.; Jemal, A.; Bray, F. Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA Cancer J. Clin.* 2021, 71, 209–249. [CrossRef]
3. van der Pol, C.C.; Moelans, C.B.; Manson, Q.F.; Batenburg, M.C.; van der Wall, E.; Rinkes, I.B.; Verkooijen, L.; Raman, V.; van Diest, P.J. Cytoplasmic DDX3 as prognosticator in male breast cancer. *Virchows Archiv* 2021, 479, 647–655. [CrossRef] [PubMed]
4. Hossain, M.S.; Ferdous, S.; Karim-Kos, H.E. Breast cancer in South Asia: A Bangladeshi perspective. *Cancer Epidemiol.* 2014, 38, 465–470. [CrossRef] [PubMed]
5. Uddin, A.K.; Khan, Z.J.; Islam, J.; Mahmud, A. Cancer care scenario in Bangladesh. *South Asian J. Cancer* 2013, 2, 102. [CrossRef]
6. Bellah, S.F.; Salam, M.A.; Karim, M.R.; Hossain, M.J.; Ashrafudoulla, M. Epidemiology of breast cancer among the female patients in Bangladesh. *Orient. Pharm. Exp. Med.* 2016, 16, 85–95. [CrossRef]

7. Arevalo, J.; González, F.A.; Ramos-Pollán, R.; Oliveira, J.L.; Lopez, M.A.G. Convolutional neural networks for mammography mass lesion classification. In Proceedings of the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milano, Italy, 25–29 August 2015; pp. 797–800.
8. Yap, M.H.; Pons, G.; Martí, J.; Ganau, S.; Sentís, M.; Zwiggelaar, R.; Davison, A.K.; Martí, R. Automated breast ultrasound lesions detection using convolutional neural networks. *IEEE J. Biomed. Health Inform.* 2017, 22, 1218–1226. [CrossRef]
9. Doi, K. Computer-aided diagnosis in medical imaging: Historical review, current status and future potential. *Comput. Med. Imaging Graph.* 2007, 31, 198–211. [CrossRef]
10. Brem, R.F.; Rapelyea, J.A.; Zisman, G.; Hoffmeister, J.W.; DeSimio, M.P. Evaluation of breast cancer with a computer-aided detection system by mammographic appearance and histopathology. *Cancer Interdiscip. Int. J. Am. Cancer Soc.* 2005, 104, 931–935. [CrossRef].
11. Schneider, M.; Yaffe, M. Better detection: Improving our chances. In Proceedings of the Digital Mammography: 5th International Workshop on Digital Mammography (IWDM), Toronto, ON, Canada, 11–14 June 2000; pp. 3–6.
12. Huang, D.; Bai, H.; Wang, L.; Hou, Y.; Li, L.; Xia, Y.; Yan, Z.; Chen, W.; Chang, L.; Li, W. The Application and Development of Deep Learning in Radiotherapy: A Systematic Review. *Technol. Cancer Res. Treat.* 2021, 20, 15330338211016386. [CrossRef]
13. Munir, K.; Elahi, H.; Farooq, M.U.; Ahmed, S.; Frezza, F.; Rizzi, A. Detection and screening of COVID-19 through chest computed tomography radiographs using deep neural networks. In *Data Science for COVID-19*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 63–73.
14. Janowczyk, A.; Madabhushi, A. Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases. *J. Pathol. Inform.* 2016, 7, 29. [CrossRef]
15. Ghorbani, A.; Ouyang, D.; Abid, A.; He, B.; Chen, J.H.; Harrington, R.A.; Liang, D.H.; Ashley, E.A.; Zou, J.Y. Deep learning interpretation of echocardiograms. *NPJ Digit. Med.* 2020, 3, 10. [CrossRef] [PubMed]
16. Hutchinson, L.; Steiert, B.; Soubret, A.; Wagg, J.; Phipps, A.; Peck, R.; Charoin, J.E.; Ribba, B. Models and machines: How deep learning will take clinical pharmacology to the next level. *CPT Pharmacomet. Syst. Pharmacol.* 2019, 8, 131. [CrossRef] [PubMed]
17. Munir, K.; Frezza, F.; Rizzi, A. Deep Learning for Brain Tumor Segmentation. In *Deep Learning for Cancer Diagnosis*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 189–201.
18. Munir, K.; Frezza, F.; Rizzi, A. Brain Tumor Segmentation Using 2D-UNET Convolutional Neural Network. In *Deep Learning for Cancer Diagnosis*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 239–248.
19. Zou, J.; Huss, M.; Abid, A.; Mohammadi, P.; Torkamani, A.; Telenti, A. A primer on deep learning in genomics. *Nat. Genet.* 2019, 51, 12–18. [CrossRef]
20. Murthy, N.S.; Bethala, C. Review paper on research direction towards cancer prediction and prognosis using machine learning and deep learning models. *J. Ambient. Intell. Humaniz. Comput.* 2021, 1–19. [CrossRef]
21. Aggarwal, R.; Sounderajah, V.; Martin, G.; Ting, D.S.; Karthikesalingam, A.; King, D.; Ashrafian, H.; Darzi, A. Diagnostic accuracy of deep learning in medical imaging: A systematic review and meta-analysis. *NPJ Digit. Med.* 2021, 4, 65. [CrossRef]
22. Xie, J.; Liu, R.; Luttrell IV, J.; Zhang, C. Deep learning based analysis of histopathological images of breast cancer. *Front. Genet.* 2019, 10, 80. [CrossRef]
23. Lehman, C.D.; Yala, A.; Schuster, T.; Dontchos, B.; Bahl, M.; Swanson, K.; Barzilay, R. Mammographic breast density assessment using deep learning: Clinical implementation. *Radiology* 2019, 290, 52–58. [CrossRef]
24. Le, H.; Gupta, R.; Hou, L.; Abousamra, S.; Fassler, D.; Torre-Healy, L.; Moffitt, R.A.; Kurc, T.; Samaras, D.; Batiste, R.; et al. Utilizing Automated Breast Cancer Detection to Identify Spatial Distributions of Tumor Infiltrating Lymphocytes in Invasive Breast Cancer. *Am. J. Pathol.* 2020, 190, 1491–1504. [CrossRef]
25. Krithiga, R.; Geetha, P. Breast cancer detection, segmentation and classification on histopathology images analysis: A systematic review. *Arch. Comput. Methods Eng.* 2021, 28, 2607–2619. [CrossRef]

- Bai, J.; Posner, R.; Wang, T.; Yang, C.; Nabavi, S. Applying deep learning in digital breast tomosynthesis for automatic breast cancer detection: A review. *Med. Image Anal.* 2021, 71, 102049. [CrossRef]
26. Qiu, Y.; Yan, S.; Gundreddy, R.R.; Wang, Y.; Cheng, S.; Liu, H.; Zheng, B. A new approach to develop computer-aided diagnosis scheme of breast mass classification using deep learning technology. *J. X-ray Sci. Technol.* **2017**, 25, 751–763
27. B. Hajipour Khire Masjidi, S. Bahmani, F. Shari4, M. Peivandi, M. Khosravani, and A. Hussein Mohammed, "CT-ML: Diagnosis of Breast Cancer Based on Ultrasound Images and Time-Dependent Feature Extraction Methods Using Contourlet Transformation and Machine Learning," *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 1493847, 15 pages, 2022.
28. Behnam Hajipour Khire Masjidi, Soufia Bahmani , Fatemeh Sharifi, Mohammad Peivandi, Mohammad Khosravani and Adil Hussein Mohammed, "CT-ML: Diagnosis of Breast Cancer Based on Ultrasound Images and Time-Dependent Feature Extraction Methods Using Contourlet Transformation and Machine Learning", *Computational Intelligence and Neuroscience*, Volume 2022, Article ID 1493847, 15 pages, <https://doi.org/10.1155/2022/1493847>