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Deep Learning-based Breast Cancer Diagnosis Method using Convolutional Neural Networks (CNNs)

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Abstract: Breast cancer (BC) remains a significant global health concern, contributing to one of the highest mortality rates among women. Early and accurate detection is paramount for improving survival rates and ensuring a healthier life. In recent years, computing and information technology advancements have revolutionized healthcare systems, particularly in disease detection and classification. This work introduces a hybrid method to enhance breast cancer classification by combining deep learning-based techniques like convolutional neural networks (CNNs) and machine learning-based classifiers. We leveraged several well-known pre-trained CNNs, including ResNet50, MobileNetV2, DenseNet121, and Xception, to capture pertinent features of breast ultrasound images and effectively catch the intricate patterns associated with malignant and benign tumors. Subsequently, these extracted features were fed into high-performance classifiers such as SVM, KNN, XGBoost, and Softmax to accurately classify breast cancer based on the well-known benchmark, the Breast Ultrasound Images (BUSI) dataset. The findings demonstrated the efficacy of our proposed method, with the DenseNet121 network, when combined with the Softmax classifier, achieving the most superior performance with the highest accuracy of 95.34% compared to other models and state-of-the-art techniques, demonstrating the robustness and reliability of the introduced method in distinguishing between malignant and benign breast tumors, thereby facilitating more informed clinical decision making.

Keywords: Breast cancer, transfer learning, DenseNet121, machine learning, classification..

1. Introduction

Breast cancer ranks among the deadliest and most dangerous diseases [1, 2], being the second largest source of death for women worldwide [3, 4]. The World Health Organization (WHO) predicted that 2.3 million women had breast cancer, and 685,000 deaths occurred internationally in 2020 [5]. Therefore, early treatment of breast cancer can be highly effective and can dramatically reduce its mortality rates. Diverse imaging methods, such as mammograms, MRI, ultrasound, histopathology, and thermography, are often used to obtain successfully well-processed images, which may help doctors distinguish the severity level of the disease and thus make quick and precise decisions [6]. Ultrasound (US) imaging is the most involved modality for assisting radiologists in evaluating and diagnosing breast cancer in females. It appears to be more portable, noninvasive, and cheaper than other medical imaging modalities [7]. However, analyzing Breast US images (BUSI) is difficult and has high inter-rate trust. For properly identifying whether breast tumors are benign or malignant, medical experts must be very knowledgeable in the highest correlation characteristics of BUSI with malignancy, for instance, cancer size, form, and vascularity.

Nevertheless, machine learning algorithms (MLAs) were extensively utilized to help radiologists distinguish breast tumors [8–10]. Deep learning techniques such as convolutional neural networks (CNNs) can analyze images naturally, identify their significant features, and generate preferred outcomes [11–14]. Conversely, these algorithms' success often depends on the quantity of training data provided. Training a CNN model from scratch is usually not recommended when data is lacking. Therefore, transfer learning (TL) approaches were introduced, and they are now the most widely used methods for constructing deep learning-based systems in medical image analysis [15, 16]. TL involves models that were first pre-trained on big datasets like ImageNet for another related task dataset (target task) [17].

This paper presents a hybrid method for precisely classifying breast tumors via deep CNN networks: ResNet50, MobileNetV2, DenseNet121, and Xception to effectively identify the most relevant features of the breast ultrasound images (BUSI) dataset. The extracted features are subsequently passed into high-performance classifiers such as SVM, KNN, XGBoost, and Softmax to select the best classifier to the best CNN model. The superiority of our proposed method was demonstrated by outperforming existing methods, providing enhancements in early diagnosis and tailored treatment.

The paper's reminder is structured as follows: Section 2 presents a detailed assessment of available research on breast cancer diagnosis. Section 3 fully discusses the materials and methods, including the dataset and methods. Section 4 examines the findings and their implications. Section 5 provides a comparison with state-of-the-art techniques. Finally, Section 6 presents the paper's conclusion.

2. Literature Review

Recently, deep learning (DL) has become gradually widespread for classifying breast cancer. In [18], a lightweight CNN (DBLCNN) based on dependencies for categorizing breast histopathology images was proposed. It was combined with pre-trained CNN architectures, including MobileNetV2 and MobileNetV3. The results showed that DBLCNN (MobileNetV2) achieved superior results compared to other models. To precisely predict breast cancer, the authors in [19] implemented an automated diagnostic system using deep CNNs to select important features of breast ultrasonography scans. The results demonstrated the proposed DeepCls subsystem effectiveness, outperforming the other subsystems (DeepRec + DeepCls, DeepCls + DeepAt, and DeepRec + DeepCls + DeepAti) with an accuracy of 94.51%.

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In [20], an auto-weighting approach (AW3M) for automated breast cancer classification was developed using multiple types of sonography, such as Shear-wave Elastography. Unlike other methods, AW3M uses reinforcement learning techniques to determine the optimal weights for different data streams rather than assigning weights arbitrarily. The suggested approach was assessed using huge multi-modal data and showed promising results. Similarly, [21] proposed a DL-based approach to accurately segment the nuclei in breast tissue images, followed by an ensemble classifier that combined the decision of three different MLAs to accurately classify breast mass, demonstrating the efficacy of the suggested methodology and outperforming the individual classifiers.

In contrast, the authors [22] have applied numerous pre-processing techniques like image enhancement and augmentation to prepare mammogram images for the scratch-built CNN architecture to learn the main features from them. The suggested method revealed a promising performance, obtaining the best accuracy of 96.52%. Likewise, the authors [23] introduced a two-level deep learning classification model. The Empirical Wavelet Transform and Variational Mode Decomposition methods first transformed the gene expression data into images. These images served as inputs for the first stage, which consisted of three separate CNN architectures. These architectures' outcomes were integrated and passed to the second stage, an MLP meta-classifier, reaching a validation accuracy of 98.08%.

A new method known as "AlexNet-BC" for categorizing breast pathologies was presented by [24], where the ImageNet dataset was employed to pre-train the proposed method, and enhanced datasets were used to refine it. The suggested approach performed better than alternative models, including VGG-16 and ResNet, with an accuracy of 86.31% when evaluated on the BreaKHis, IDC, and UCSB datasets. Furthermore, the authors in [25] developed a pipeline approach to enhance the prediction of CBIS-DDSM mammography images. The approach involved training individual task-specific models and fusing their predictions with relevant features. The developed pipeline had a comparable performance with an AUC of 96.20%. Finally, the authors [26] used a cloud-based Internet of Medical Things (IoMT) network to predict and identify various breast mass stages, reaching the best accuracy of 97.81%.

3. Materials and Methods

This paper introduces a hybrid method for precisely classifying breast tumors using different deep CNN networks, including ResNet50, MobileNetV2, DenseNet121, and Xception, to effectively extract the key characteristics the breast ultrasound images (BUSI) dataset, as illustrated in Fig. 1. The extracted features are passed through several high-performance machine learning classifiers, including SVM, KNN, XGBoost, and Softmax, obtaining the best classification results. Our method is verified by considering several aspects and experiments.

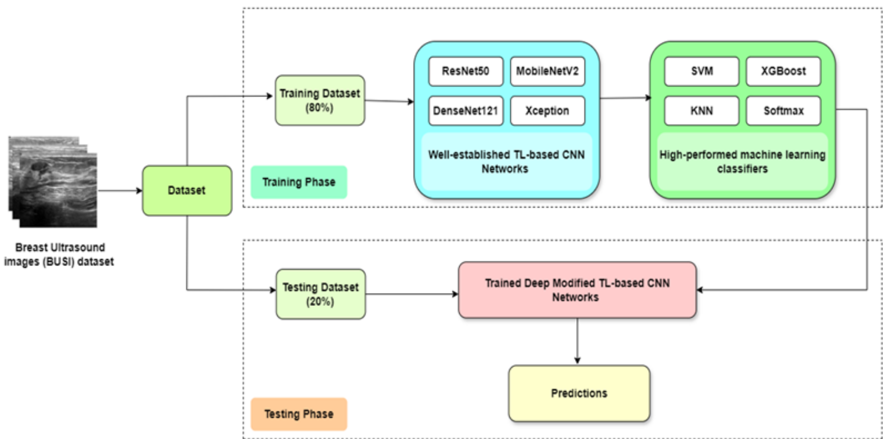

Fig. 1. Scheme of the proposed breast cancer classification method.

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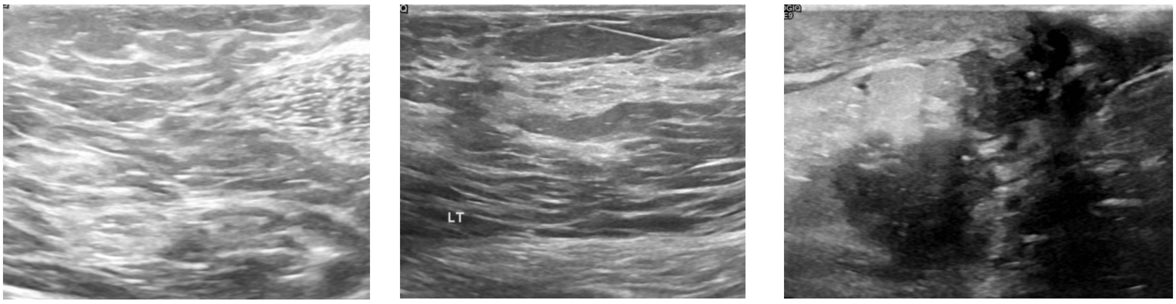
3.1 Dataset description

The breast ultrasound images (BUSI) is a challenging dataset that comprises 780 ultrasound images of women 25-75 years of age, resized to 500 × 500 pixels with the PNG format [35], and they were classified into benign, malignant, and normal classifications with 487, 210, and 177 images. These images were acquired using advanced ultrasound scanning systems—LOGIQ E9 and LOGIQ E9 Agile—at Baheya Hospital in Cairo, Egypt, adhering to standardized imaging protocols to maintain consistency and quality. Fig. 2 presents representative samples from each class in the BUSI dataset, highlighting its variability and complexity.



(a) (b) (c)

Fig. 2. Samples from the breast US images (BUSI) dataset: (a) normal, (b) benign, and (c) malignant.

3.2 Transfer learning(TL)

TL aims to adapt a model trained on one problem to another that is similar, offering reduced training time. Numerous CNN architectures have been discovered based on the ImageNet challenge and used in various image classification tasks through transfer learning. In this study, four pre-trained CNNs, including ResNet50, MobileNetV2, DenseNet121, and Xception, were conducted to capture the most significant features of the BUSI's images.

3.2.1 ResNet50 network

ResNet50 [28] is one of the most common ResNet architectures, consisting of 48 Convolution layers, a max pool, and an average pool layer with an input size of 256x256, as presented in Fig. 3. In 2015, ResNet won the ImageNet challenge over other architectures and was and was subsequently employed in several computer vision applications, including image segmentation and classification. Using skip connections between layers helps reduce the number of parameters while addressing the vanishing gradient problem associated with extremely deep CNNs [29].

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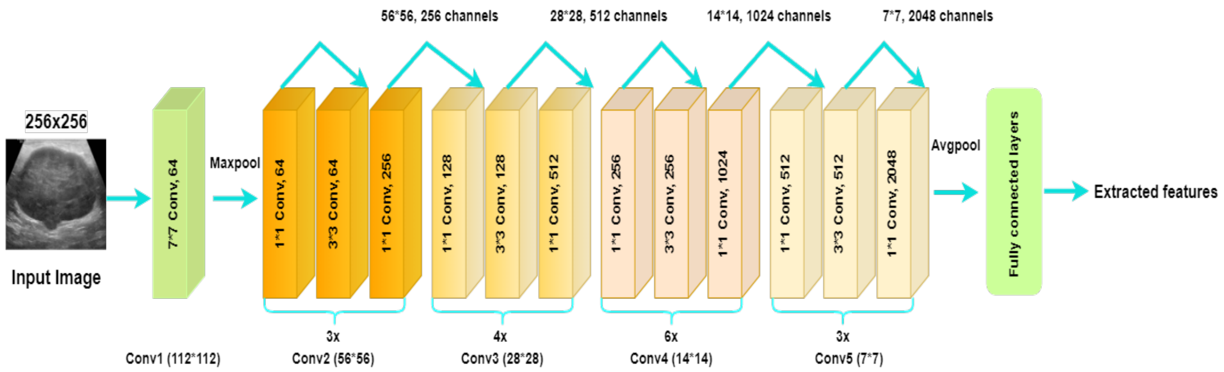

Fig. 3. The deep feature extractor ResNet50 architecture.

3.2.2 MobileNetV2 network

MobileNetV2 is a deep CNN model introduced by Google for mobile and embedded vision applications [30, 31], which was designed to be more efficient and faster than traditional computer vision models. MobileNetV2 uses depthwise separable convolutions, which are computationally more efficient than normal convolutions, to reduce the parameters number and FLOPS (floating-point operations) essential for inference. Additionally, MobileNetV2 adds a linear bottleneck layer to the end of each residual block (as seen in Fig. 4), which helps reduce the computation needed for inference [32, 33].

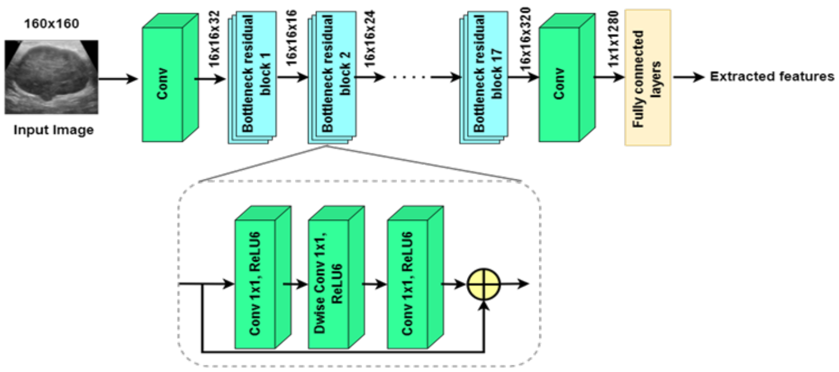

Fig. 4. The deep feature extractor MobileNetV2 architecture.

3.2.3 DenseNet121 network

Gao Huang et al. [34] created a deep learning architecture named "DenseNet121" in 2017. It is designed to beat traditional networks such as ResNet and Inception by introducing a dense block, allowing information to flow more freely between different layers in the network (see Fig. 5). This improves performance by avoiding the vanishing gradients problem while significantly reducing the number of parameters required to learn at each layer [29].

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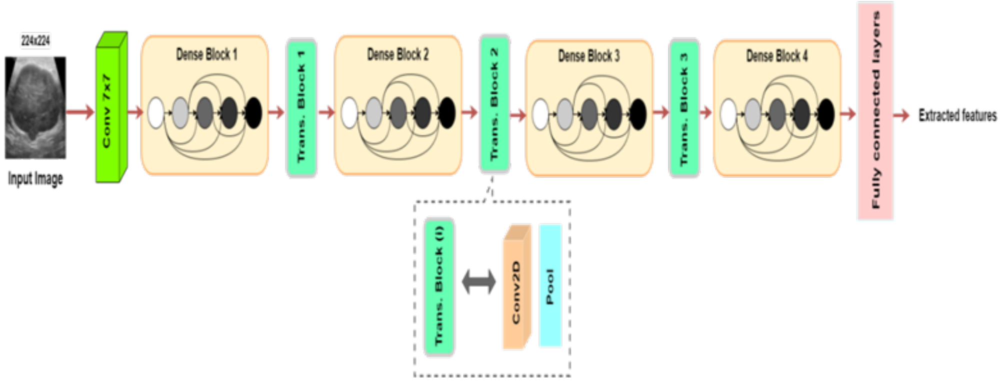

Fig. 5. The deep feature extractor DenseNet121 architecture.

3.2.4 Xception network

The Xception (i.e., Extreme Inception) model [35] was developed to improve upon the Inception-V3 architecture based on depthwise separable convolutions to independently incorporate the spatial and channel dimensions of the image during training [36]. It has been used with great success in various medical imaging fields. The Xception feature extractor's architecture is described in Fig. 6.

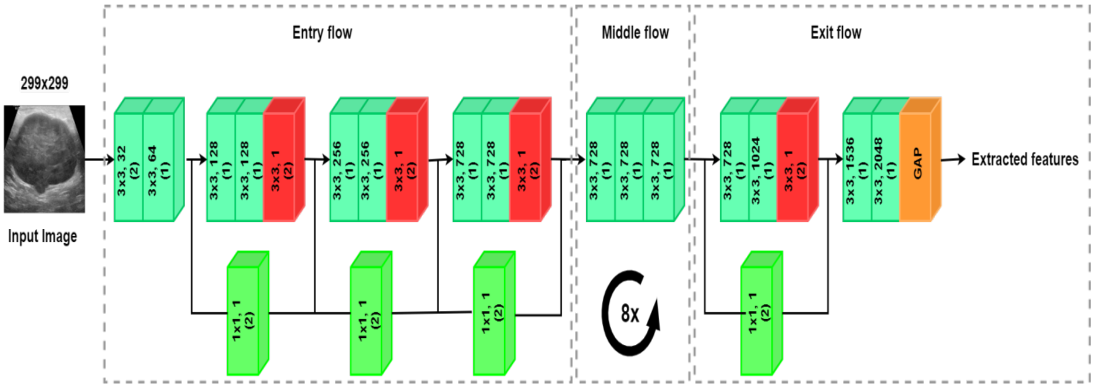

Fig. 6. The deep feature extractor Xception architecture.

3.3 Machine learning algorithms (MLAs)

Several commonly used MLAs, namely support vector machine (SVM), k-nearest neighbor (KNN), XGBoost, and softmax, are implemented for the ultimate classification of breast cancer.

The SVM [37] is a supervised MLA utilized for classification applications. It creates a hyper-plane to distinct two or more categories. We have implemented the SVM as a classifier of all feature extractors with its default hyper-parameters.

The KNN [38] is an effective MLA for classification tasks. KNN does not require a training phase; it only needs a distance function for the inputs as it works based on the data instances and their features' similarities. The hyperparameters of the KNN were also set to their default values.

The eXtreme Gradient Boosting (XGBoost) algorithm, introduced by Chen and Guestrin in 2016 [39], is considered a peak-performance classifier. XGBoost combines multiple weak trees with low-performance rates to create a strong one. All hyperparameters were set to their default values.

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4. Result and Discussion

Multiple experimentations were implemented to correctly measure the performance of the proposed method by assessing several well-established pre-trained CNNs' performance with different classifiers to select the best classifier with the best pre-trained model regarding their performance based on several regular assessment measures, such as accuracy, precision, and F1-score. The BUSI dataset has been distributed into train and test splits using the 80-20% splitting standard, respectively.

4.1 Performance evaluation

The confusion matrix (CM) analyzes the performance of a classification model on testing data samples with known true values. Its columns represent samples in a predicted class, while the rows represent instances in an actual class (or vice versa) [40–42]. For performance analysis, several criteria, including accuracy, precision, and the F1-score, are used, as illustrated in (1), (2), and (3).

4.1.1 Accuracy

It assesses the general correctness of the model's predictions. It is computed as the proportion of accurately predicted cases (both positive and negative) to the total number of samples.

$$Accuracy = (TP+TN) / (TP+TN+FP+FN) \quad (1)$$

4.1.2 Precision

Precision assesses the percentage of correctly predicted positive examples out of all instances predicted as positive. It illustrates how well the model can avoid false positives.

$$Precision = TP / (TP+FP) \quad (2)$$

4.1.3 F1-score

This metric is the harmonic mean of precision and sensitivity, offering a balanced degree. It shows the model's ability to identify positive instances while avoiding false positives, which is very helpful when working with imbalanced datasets.

$$F1\text{-}score = 2*TP / (2*TP+FN+FP) \quad (3)$$

Where,

TP (True Positive): The label's actual value is True, as is the predicted value.

TN (True Negative): The label's actual value, as is the predicted value, is false.

FN (False Negative): The label's actual value is True, while the predicted value is False.

FP (False Positive): The label's actual value is False, while the predicted value is True.

4.2 Performance assessment

We compared the effectiveness of multiple prominent pre-trained CNNs, such as ResNet50, MobileNetV2, DenseNet121, and Xception. Table 1 presents the performance of these networks when coupled with various classifiers, including SVM, KNN, XGBoost, and Softmax, evaluated on the BUSI dataset. The Softmax classifier consistently yielded substantial performance rates across all CNN architectures. Specifically, DenseNet121 achieved the highest accuracy of 95.34%, representing a 7% improvement compared to its best-

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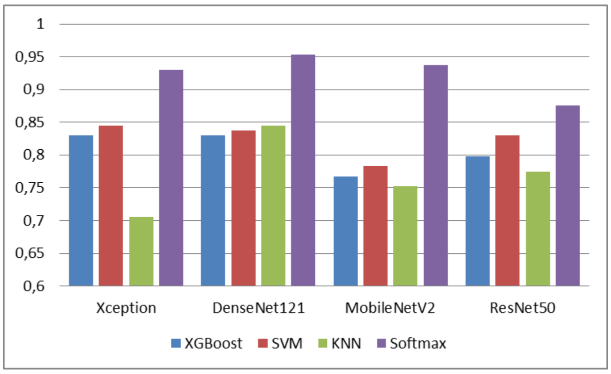
performing counterpart using XGBoost, highlighting the effectiveness of DenseNet121's feature representation for the given classification task.

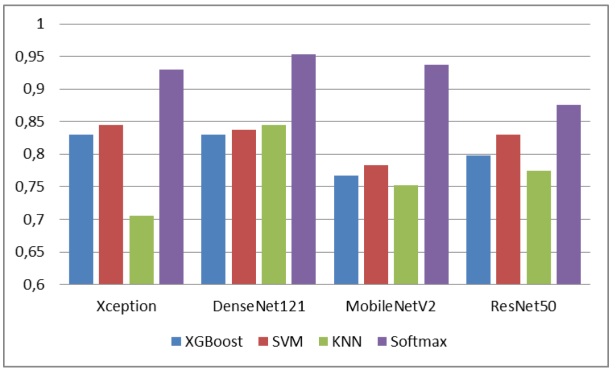
Table 1. Performance evaluation of different deep CNN networks with various classifiers.

Deep CNN networks	**Machine learning classifiers**	**Performance (%)**		
		Accuracy	**Precision**	**F1-score**
ResNet50	SVM	82.95	83.33	81.88
	KNN	77.52	76.85	76.93
	XGBoost	79.84	79.46	78.82
	Softmax	87.59	84.21	80.00
MobileNetV2	SVM	78.29	79.65	75.66
	KNN	75.19	75.88	75.47
	XGBoost	76.74	76.17	74.99
	Softmax	93.79	94.73	90.00
DenseNet121	SVM	83.72	84.48	82.60
	KNN	84.50	84.48	83.87
	XGBoost	82.95	82.65	82.71
	Softmax	95.34	90.90	93.02
Xception	SVM	84.50	85.71	83.32
	KNN	70.54	69.31	69.64
	XGBoost	82.95	83.33	81.88
	Softmax	93.02	94.59	88.60

A visual performance comparison of various pre-trained CNN architectures (ResNet50, MobileNetV2, DenseNet121, and Xception) is evaluated in Fig. 7. This evaluation used several peak-performance algorithms: XGBoost, SVM, KNN, and Softmax on the BUSI dataset. Notably, the DenseNet121 architecture, paired with a Softmax classifier, achieved the highest performance metrics, including accuracy (95.34%), precision (90.90%), and F1-score (93.02%). This analysis underscores the significant influence of CNN architecture and classifier choice on diagnostic accuracy, thereby guiding the development of effective computer-aided diagnostic tools. Fig. 8 further clarifies the effectiveness of these CNNs with the Softmax classifier based on different metrics. DenseNet121 consistently outperforms the other networks, indicating higher feature extraction ability. While MobileNetV2 obtains a competitive accuracy of 93.79%, a slightly decreased F1-score of 90.00% suggests a potential balance between precision and sensitivity. These results prove our methodology's efficiency for accurately classifying breast tumors.



(a)



(b)

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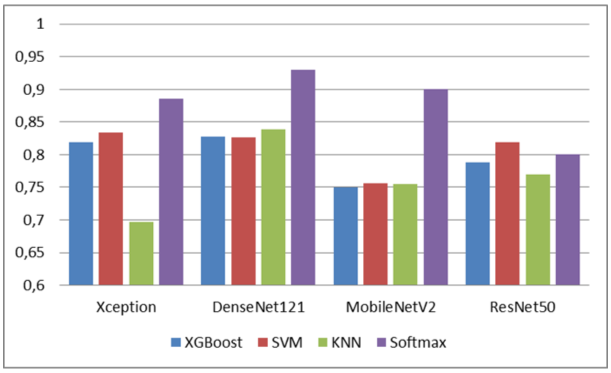

(c)

Fig. 7. Performance comparison of various CNN feature extractors with different classifiers using standard criteria: (a) accuracy, (b) precision, and (c) F1-score.

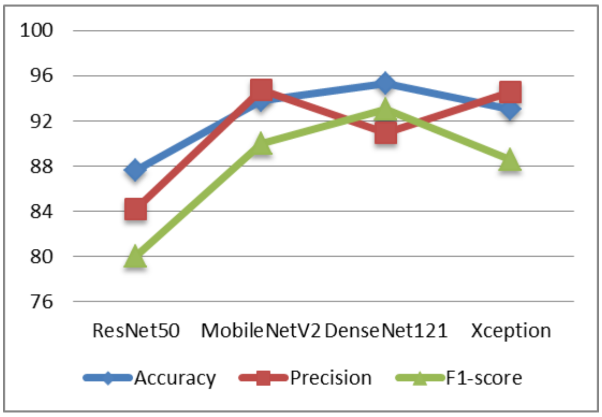

Fig. 8. Performance assessment of different deep CNNs and the softmax classifier.

5. Comparison with Existing Methods

This section performed a comparison study with several existing techniques reported in recent studies concentrating on breast tumor classification to prove the efficiency of the proposed methodology. These studies were selected based on their utilization of similar experimental protocols, datasets, and evaluation metrics for performance assessment. Table 2 presents a comparative performance analysis detailing the compared methods and their reported accuracy.

Table 2. Performance comparison with similar studies.

References	Dataset	Methods	Accuracy (%)
[6]	BUSI	TL-based deep representation scaling (DRS)	91.5
[7]		ResNet50	73.72
[19]		DeepCls	94.51
Ours		DenseNet121 Network with Softmax classifier	95.34

6. Conclusion

This paper proposes a hybrid methodology for precisely classifying breast tumors, demonstrating how well deep learning techniques performed, and comparing the efficiency of various CNN architectures as feature extractors combined with different classifiers (SVM, KNN, XGBoost, and Softmax) to identify the best combination. The results demonstrated that integrating DenseNet121 with a Softmax classifier achieved comparable performance on the BUSI dataset, yielding the best accuracy of 95.34%. These findings significantly outperformed existing methods, demonstrating the possibility of merging DL-based deep learning techniques and MLAs for boosting the efficacy of breast cancer detection systems, leading to earlier and more accurate diagnoses, eventually boosting patient outcomes, and saving healthcare expenditures connected with delayed treatments. Future research will seek to confirm these results on other datasets and examine the predictions for clinical application.

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Conflict of Interest

The authors declare no conflict of interest.

References

[1] Z. Yang, L. Ran, S. Zhang, Y. Xia, and Y. Zhang, “EMS-Net: Ensemble of multiscale convolutional neural networks for classification of breast cancer histology images,” Neurocomputing, vol. 366, pp. 46-53, 2019.
[2] A. Sahu, P. K. Das, and S. Meher, “High accuracy hybrid CNN classifiers for breast cancer detection using mammogram and ultrasound datasets,” Biomedical Signal Processing and Control, vol. 80, 104292, 2023.
[3] D. Muduli, R. Dash, and B. Majhi, “Automated diagnosis of breast cancer using multi-modal datasets: A deep convolution neural network-based approach,” Biomedical Signal Processing and Control, vol. 71, 102825, 2022.
[4] R. A. Dar, M. Rasool, and A. Assad, “Breast cancer detection using deep learning: Datasets, methods, and challenges ahead,” Computers in biology and medicine, vol. 149, 106073, 2022.
[5] World Health Organization (WHO), [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/breast-cancer. [Accessed: March 2023].
[6] M. Byra, “Breast mass classification with transfer learning based on scaling of deep representations,” Biomedical Signal Processing and Control, vol. 69, 102828, 2021.
[7] M. S. K. Inan, F. I. Alam, and R. Hasan, “Deep integrated pipeline of segmentation guided classification of breast cancer from ultrasound images,” Biomedical Signal Processing and Control, vol. 75, 103553, 2022.
[8] Y. L. Huang, “Computer-aided diagnosis using neural networks and support vector machines for breast ultrasonography,” Journal of Medical Ultrasound, vol. 17, no. 1, pp. 17-24, 2009.
[9] M. Khashei and N. Bakhtiarvand, “A novel discrete learning-based intelligent methodology for breast cancer classification purposes,” Artificial Intelligence in Medicine, vol. 139, 102492, 2023.
[10] G. G. Wu, L. Q. Zhou, J. W. Xu, J. Y. Wang, Q. Wei, Y. B. Deng, ... and C. F. Dietrich, “Artificial intelligence in breast ultrasound,” World Journal of Radiology, vol. 11, no. 2, 19, 2019.
[11] A. Mustaqeem,A. Javed,T. Fatima,”An Efficient Brain Tumor Detection Algorithm Using Watershed & Thresholding Based Segmentation”, IJIGSP, vol.4, no.10, pp.34-39, 2012. DOI: 10.5815/ijigsp.2012.10.05.
[12] P. E. Jebarani, N. Umadevi, H. Dang, and M. Pomplun, “A novel hybrid K-means and GMM machine learning model for breast cancer detection,” IEEE Access, vol. 9, pp. 146153-146162, 2021.
[13] M. Jha, R. Gupta, R. Saxena, “Denoising of Non-Small Cell Lung Cancer CT-scans through Fractional Fourier Transform for a Non-invasive Diagnostic Model”, International Journal of Image, Graphics and Signal Processing (IJIGSP), Vol.17, No.1, pp. 88-106, 2025. DOI:10.5815/ijigsp.2025.01.07.
[14] M. W. P. Maduranga, and D. Nandasena, “Mobile-Based Skin Disease Diagnosis System Using Convolutional Neural Networks (CNN)”, International Journal of Image, Graphics and Signal Processing (IJIGSP), Vol.14, No.3, pp. 47-57, 2022.DOI: 10.5815/ijigsp.2022.03.05.
[15] M. A. Morid, A. Borjali, and G. Del Fiol, “A scoping review of transfer learning research on medical image analysis using ImageNet,” Computers in biology and medicine, vol. 128, 104115, 2021.
[16] N. F. Aurna, M. A. Yousuf, K. A. Taher, A. K. M. Azad, and M. A. Moni, “A classification of MRI brain tumor based on two stage feature level ensemble of deep CNN models,” Computers in biology and medicine, vol. 146, 105539, 2022.
[17] X. Yu, J. Wang, Q. Q. Hong, R. Teku, S. H. Wang, and Y. D. Zhang, “Transfer learning for medical images analyses: A survey,” Neurocomputing, vol. 489, pp. 230-254, 2022.
[18] C. Wang, W. Gong, J. Cheng, and Y. Qian, “DBLCNN: Dependency-based lightweight convolutional neural network for multi-classification of breast histopathology images,” Biomedical Signal Processing and Control, vol. 73, 103451, 2022.
[19] X. Qi, F. Yi, L. Zhang, Y. Chen, Y. Pi, Y. Chen, ... and Z. Yi, “Computer-aided diagnosis of breast cancer in ultrasonography images by deep learning,” Neurocomputing, vol. 472, pp. 152-165, 2022.
[20] R. Huang, Z. Lin, H. Dou, J. Wang, J. Miao, G. Zhou, ... and D. Ni, “AW3M: An auto-weighting and recovery framework for breast cancer diagnosis using multi-modal ultrasound,” Medical image analysis, vol. 72, 102137, 2021.
[21] L. B. Mahanta, E. Hussain, N. Das, L. Kakoti, and M. Chowdhury, “IHC-Net: A fully convolutional neural network for automated nuclear segmentation and ensemble classification for Allred scoring in breast pathology,” Applied Soft Computing, vol. 103, 107136, 2021.

Received: February 24, 2026 Published: June 30, 2026

[22] E. M. El Houby and N. I. Yassin, “Malignant and nonmalignant classification of breast lesions in mammograms using convolutional neural networks,” Biomedical Signal Processing and Control, vol. 70, 102954, 2021.
[23] A. Das, M. N. Mohanty, P. K. Mallick, P. Tiwari, K. Muhammad, and H. Zhu, “Breast cancer detection using an ensemble deep learning method,” Biomedical Signal Processing and Control, vol. 70, 103009, 2021.
[24] M. Liu, L. Hu, Y. Tang, C. Wang, Y. He, C. Zeng, ... and W. Huo, “A deep learning method for breast cancer classification in the pathology images,” IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 10, pp. 5025-5032, 2022.
[25] M. Wimmer, G. Sluiter, D. Major, D. Lenis, A. Berg, T. Neubauer, and K. Bühler, “Multi-task fusion for improving mammography screening data classification,” IEEE Transactions on Medical Imaging, vol. 41, no. 4, pp. 937-950, 2021.
[26] S. Y. Siddiqui, A. Haider, T. M. Ghazal, M. A. Khan, I. Naseer, S. Abbas, ... and K. Ateeq, “IoMT cloud-based intelligent prediction of breast cancer stages empowered with deep learning,” IEEE Access, vol. 9, pp. 146478-146491, 2021.
[27] W. Al-Dhabyani, M. Gomaa, H. Khaled, and A. Fahmy, “Dataset of breast ultrasound images,” Data in brief, vol. 28, 104863, 2020.
[28] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778, 2016.
[29] S. Boumaraf, X. Liu, Z. Zheng, X. Ma, and C. Ferkous, “A new transfer learning based approach to magnification dependent and independent classification of breast cancer in histopathological images,” Biomedical Signal Processing and Control, vol. 63, 102192, 2021.
[30] S. Majumdar, P. Pramanik, and R. Sarkar, “Gamma function based ensemble of CNN models for breast cancer detection in histopathology images,” Expert Systems with Applications, vol. 213, 119022, 2023.
[31] A. K. Poyraz, S. Dogan, E. Akbal, and T. Tuncer, “Automated brain disease classification using exemplar deep features,” Biomedical Signal Processing and Control, vol. 73, 103448, 2022.
[32] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, “Mobilenetv2: Inverted residuals and linear bottlenecks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4510-4520, 2018.
[33] M. E. Sahin, “Deep learning-based approach for detecting COVID-19 in chest X-rays,” Biomedical Signal Processing and Control, vol. 78, 103977, 2022.
[34] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700-4708, 2017.
[35] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1251-1258, 2017.
[36] K. Shaheed, A. Mao, I. Qureshi, M. Kumar, S. Hussain, I. Ullah, and X. Zhang, “DS-CNN: A pre-trained Xception model based on depth-wise separable convolutional neural network for finger vein recognition,” Expert Systems with Applications, vol. 191, 116288, 2022.
[37] C. Cortes and V. Vapnik, “Support-vector networks,” Machine learning, vol. 20, pp. 273-297, 1995.
[38] O. Kramer, “Dimensionality reduction with unsupervised nearest neighbors,” Dimensionality reduction with unsupervised nearest neighbors, vol. 51, pp. 13-23, 2013.
[39] T. Chen and C. Guestrin, “Xgboost: A scalable tree boosting system,” in Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, pp. 785-794, 2016.
[40] T. Beghriche, M. Djerioui, Y. Brik, B. Attallah, S. B. Belhaouari, “An efficient prediction system for diabetes disease based on deep neural network,” Complexity, vol. 2021, no. 1, p. 6053824, 2021.
[41] J. Han, J. Pei, and H. Tong, Data mining: concepts and techniques, Morgan Kaufmann, 2022.
[42] M. Grandini, E. Bagli, and G. Visani, “Metrics for multi-class classification: an overview,” arXiv preprint arXiv:2008.05756, 2020.