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Deep-modified transfer learning-based CNN networks for enhanced breast cancer prediction

Redes CNN baseadas em aprendizado de transferência profundamente modificado para melhorar a previsão do câncer de mama

Redes CNN basadas en aprendizaje profundo modificado para mejorar la predicción del cáncer de mama

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Tawfiq Beghriche
PhD Student in Electronics
Institution: University Mohamed Boudiaf of M'sila
Address: M'sila, Algeria
E-mail: tawfiq.beghriche@univ-msila.dz

Mohamed Djerioui
PhD in Electronics
Institution: University Mohamed Boudiaf of M'sila
Address: M'sila, Algeria
E-mail: mohamed.djerioui@univ-msila.dz

Youcef Brik
PhD in Electronics
Institution: University Mohamed Boudiaf of M'sila
Address: M'sila, Algeria
E-mail: youcef.brik@univ-msila.dz

Bilal Attallah
PhD in Electronics
Institution: University Mohamed Boudiaf of M'sila
Address: M'sila, Algeria
E-mail: bilal.attallah@univ-msila.dz

ABSTRACT
Breast cancer (BC) is one of the most fatal forms of cancer, making it a significant contributor to mortality rates worldwide. Early detection and timely treatment of breast cancer are crucial in reducing its mortality rate. To ensure a healthy lifestyle, it is essential to develop systems that can accurately diagnose breast cancer. Recent advances in modern computing and information technologies have enabled significant progress in the early detection and prediction of diseases within healthcare systems. This study proposes a method for precise and automatic

breast cancer prediction using deep-modified transfer learning-based Convolutional Neural Networks (CNNs). The CNN architectures employed include ResNet50, MobileNetV2, DenseNet121, and Xception, which serve as feature extractors to capture the most relevant features of breast Ultrasound images (BUSI). These extracted features are then accurately classified as benign or malignant using various high-performance classifiers, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), XGBoost, and Softmax. The experimental results demonstrate that the proposed deep modified DenseNet121 network with the Softmax classifier outperformed other models and existing techniques. This latter achieved remarkable performance metrics, including an accuracy of 95.34%, a precision of 90.90%, and an F1 score of 93.02%. These results highlight the effectiveness of our approach in enhancing the accuracy of breast cancer prediction. The superior performance of the proposed method provides significant improvements in decision-making speed and reduces the time, effort, and laboratory resources required for healthcare services. Consequently, this method has the potential to significantly enhance early diagnosis and enable more tailored treatment plans, ultimately contributing to better patient outcomes and reducing the overall mortality rates associated with breast cancer.

Keywords: Transfer Learning. CNNs. Machine Learning (ML). Breast Cancer. Classification.

RESUMO

O câncer de mama (CM) é uma das formas mais fatais de câncer, o que o torna um contribuinte significativo para as taxas de mortalidade em todo o mundo. A detecção precoce e o tratamento oportuno do câncer de mama são fundamentais para reduzir sua taxa de mortalidade. Para garantir um estilo de vida saudável, é essencial desenvolver sistemas que possam diagnosticar com precisão o câncer de mama. Os recentes avanços nas modernas tecnologias de computação e informação permitiram um progresso significativo na detecção precoce e na previsão de doenças nos sistemas de saúde. Este estudo propõe um método para a previsão precisa e automática do câncer de mama usando Redes Neurais Convolucionais (CNNs) baseadas em aprendizagem de transferência profunda modificada. As arquiteturas de CNN empregadas incluem ResNet50, MobileNetV2, DenseNet121 e Xception, que servem como extratores de recursos para capturar os recursos mais relevantes das imagens de ultrassom de mama (BUSI). Esses recursos extraídos são então classificados com precisão como benignos ou malignos usando vários classificadores de alto desempenho, incluindo Support Vector Machine (SVM), K-Nearest Neighbors (KNN), XGBoost e Softmax. Os resultados experimentais demonstram que a rede DenseNet121 profunda modificada proposta com o classificador Softmax superou outros modelos e técnicas existentes. Esse último alcançou métricas de desempenho notáveis, incluindo uma precisão de 95,34%, uma exatidão de 90,90% e uma pontuação F1 de 93,02%. Esses resultados destacam a eficácia da nossa abordagem para aumentar a precisão da previsão de câncer de mama. O desempenho superior do método proposto proporciona melhorias significativas na velocidade da tomada de decisões e reduz o tempo, o esforço e os recursos laboratoriais necessários para os serviços de saúde. Consequentemente, esse método tem o potencial de melhorar significativamente o diagnóstico precoce e permitir planos de tratamento mais personalizados, contribuindo, em última análise, para melhores resultados para os pacientes e reduzindo as taxas gerais de mortalidade associadas ao câncer de mama.

Palavras-chave: Aprendizagem por Transferência. CNNs. Aprendizagem de Máquina (ML). Câncer de Mama. Classificação.

RESUMEN

El cáncer de mama (CM) es una de las formas más mortales de cáncer, por lo que contribuye significativamente a las tasas de mortalidad en todo el mundo. La detección precoz y el tratamiento oportuno del cáncer de mama son cruciales para reducir su tasa de mortalidad. Para garantizar un estilo de vida saludable, es esencial desarrollar sistemas capaces de diagnosticar con precisión el cáncer de mama. Los recientes avances en las modernas tecnologías informáticas y de la información han permitido un progreso significativo en la detección precoz y la predicción de enfermedades dentro de los sistemas sanitarios. Este estudio propone un método para la predicción precisa y automática del cáncer de mama utilizando redes neuronales convolucionales (CNN) basadas en el aprendizaje por transferencia modificado en profundidad. Las arquitecturas CNN empleadas incluyen ResNet50, MobileNetV2, DenseNet121 y Xception, que sirven como extractores de características para capturar las características más relevantes de las imágenes de ultrasonido de mama (BUSI). A continuación, estas características extraídas se clasifican con precisión como benignas o malignas utilizando varios clasificadores de alto rendimiento, como Support Vector Machine (SVM), K-Nearest Neighbors (KNN), XGBoost y Softmax. Los resultados experimentales demuestran que la red profunda DenseNet121 modificada propuesta con el clasificador Softmax superó a otros modelos y técnicas existentes. Este último logró métricas de rendimiento notables, incluyendo una exactitud del 95,34%, una precisión del 90,90% y una puntuación F1 del 93,02%. Estos resultados ponen de manifiesto la eficacia de nuestro enfoque para mejorar la precisión de la predicción del cáncer de mama. El rendimiento superior del método propuesto proporciona mejoras significativas en la velocidad de toma de decisiones y reduce el tiempo, el esfuerzo y los recursos de laboratorio necesarios para los servicios sanitarios. En consecuencia, este método tiene el potencial de mejorar significativamente el diagnóstico precoz y permitir planes de tratamiento más personalizados, contribuyendo en última instancia a mejorar los resultados de los pacientes y a reducir las tasas de mortalidad global asociadas al cáncer de mama.

Palabras clave: Aprendizaje de Transferencia. CNNs. Aprendizaje Automático (ML). Cáncer de Mama. Clasificación.

1 INTRODUCTION

Breast cancer (BC) is one of the deadliest and most dangerous diseases (Yang, 2019), (Sahu, 2023). It is globally the second-leading cause of death after lung cancer for females (Muduli, 2022), (Dar, 2022). The World Health

Organization (WHO) predicted that 2.3 million women have been affected by BC and 685,000 deaths internationally in 2020 (WHO, 2023). Therefore, early treatment of breast cancer can be highly effective and can dramatically reduce its mortality rates . A variety of BC imaging modalities such as mammography, magnetic resonance imaging (MRI), Ultrasound, Histopathology, and Thermography are often incorporated to obtain successfully well-processed images. This may help doctors to distinguish the severity level of the disease and thus make quick and precise decisions (Byra, 2021).

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 (Inan, 2022). However, the analysis of Breast US images (BUSI) is difficult and has a high level of 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 techniques have been widely used to assist radiologists in distinguishing breast tumors (Huang, 2009), (Khashei, 2023), (Wu, 2019), (Khandezamin, 2020), (Jebarani, 2021), (Bacha, 2022). Deep convolutional neural networks (CNNs) can process input images naturally to identify their significant features and generate desired outcomes (Flores, 2015). However, the performance of these methods is often linked to the amount of training data available. Training a CNN model from scratch is usually not recommended when there is a lack of data. To address this issue, transfer learning techniques have been proposed and are currently the most commonly used methods for developing deep learning-based systems in medical image analysis (Morid, 2021), (Aurna, 2022). Transfer learning involves models that have been initially trained on large datasets such as ImageNet for another related task dataset (target task) (Yu, 2022).

This research aims to develop a precise and automated method for breast cancer prediction with the following objectives:

1. employing deep-modified transfer learning-based CNN networks, including ResNet50, MobileNetV2, DenseNet121, and Xception to effectively extract relevant features from the BUSI dataset;

2. feeding the extracted features into high-performance classifiers such as SVM, KNN, XGBoost, and Softmax to accurately classify them as benign or malignant;
3. showcasing the superiority of the proposed method, outperforming existing methods using the same dataset, experimental protocol, and performance metrics;
4. Providing significant improvements in the early diagnosis of breast cancer and enabling more personalized treatment plans.

The remaining sections of this article are organized as follows: Section 2 presents a comprehensive overview of existing studies in breast cancer diagnosis. Section 3 provides a detailed description of the materials and methodology used, including the dataset and methods. Section 4 deals with the obtained results and discussion. A comparison with the state-of-the-art methods is discussed in Section 5. Finally, Section 6 includes the conclusion of the paper.

2 LITERATURE REVIEW

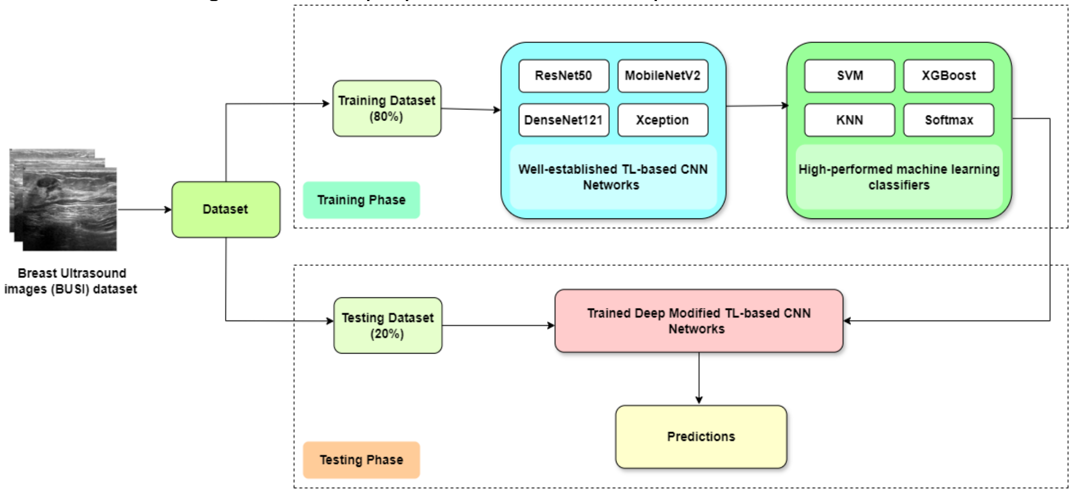
Recently, deep learning has become increasingly popular for classification of breast cancer. In (Wang, 2022), a lightweight convolutional neural network (DBLCNN) based on dependencies for the categorization of breast histopathology images was proposed. This was combined with transfer learning models such as MobileNetV2 and MobileNetV3. The results showed that DBLCNN (MobileNetV2) achieved superior results compared to other models. The authors in (Qi, 2022) have introduced an automated diagnosis system to improve the accuracy of breast cancer prediction. This system utilized deep convolutional neural networks (CNNs) to extract important features from breast ultrasonography images. The results showed that the proposed DeepCls subsystem was superior to other subsystems (DeepRec + DeepCls, DeepCls + DeepAt, and DeepRec + DeepCls + DeepAti) with an accuracy of 94.51%. Likewise, in (Huang, 2021) an Auto-Weighting framework (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 proposed method was evaluated using a large multi-modal dataset and showed promising results. In a similar manner, (Mahanta, 2021) proposed a Deep Learning (DL) based approach for nuclear segmentation and ensemble classification. They used a deep learning network to accurately segment the nuclei in breast tissue images, followed by an ensemble classifier that combined the decision of three different machine learning algorithms for breast mass classification. The results showed that the proposed method outperformed the individual classifiers. Correspondingly, The authors (El Houby, 2021) have applied numerous pre-processing techniques like image enhancement, augmentation, and more have been conducted to prepare mammogram images for the scrarch-built CNN architecture to learn the main features from them. The proposed system showed promising performance, with an accuracy of 96.52%. Whereas, (Das, 2022) introduced a two-level deep learning classification model. The gene expression data was first transformed into images using each of the Empirical Wavelet Transform (EWT) and Variational Mode Decomposition (VMD) methods. These images served as inputs for the first stage, which consisted of three separate CNN architectures. The outputs from the three architectures were combined and fed into the second stage, which was an MLP meta-classifier. The model achieved a validation accuracy of 98.08%. Besides, (Liu, 2022) proposed a novel framework for breast pathology classification called "AlexNet-BC". This model was pre-trained on the ImageNet dataset and then fine-tuned using an augmented dataset. The proposed method was tested on the BreaKHis, IDC, and UCSB Datasets and outperformed other models, including VGG-16 and ResNet, with an accuracy of 86.31%. In (Wimmer, 2021), a pipeline approach was developed to enhance the prediction of CBIS-DDSM mammography images. The approach involved training individual task-specific models and fusing their predictions and relevant features. The developed pipeline had comparable performance with an AUC of 96.20%. Finally, the authors (Siddiqui, 2021) implemented an Internet of Medical Things (IoMT) cloud-based model for predicting and identifying different breast mass stages. The model achieved a highest accuracy of 97.81%.

3 MATERIALS AND METHODOLOGY

In Figure 1, a schematic diagram of the proposed method is depicted, where deep modified transfer learning-based CNN networks are introduced to detect breast cancer tumors. First, the breast US images (BUSI) are fed to several feature extractors such as ResNet50, MobileNetV2, DenseNet121, and Xception. The extracted features are then fed into different high performance classifiers including SVM, KNN, XGBoost, and Softmax to obtain the best classification predictions. The proposed approach is verified considering several aspects and experiments.

Figure 1 – The proposed breast cancer prediction method.

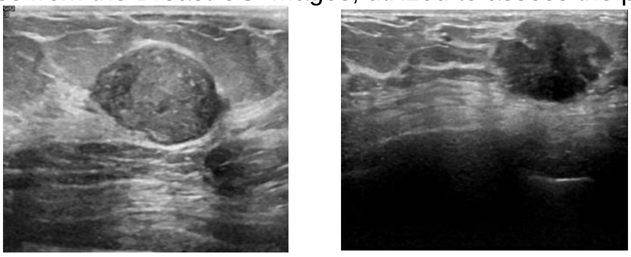


Source: Authors.

3.1 DATASET DESCRIPTION

In this study, we have conducted the breast US images (BUSI) dataset (Al-Dhabyani, 2020) to evaluate the efficiency of our proposed framework. It is a challenging dataset involving women aged 25 to 75 years old. It consists of 647 grayscale breast US images labeled as Benign (487 pictures), and Malignant (210 pictures) with the PNG extension. This latter was gathered throughout normal scanning at the Baheya Hospital in Cairo, Egypt, using LOGIQE9, LOGIQ E9 Agile US scanners. This latter was divided into two parts with 80 percent for training and the remaining 20 percent for testing. Figure 2 presents some samples concerning both benign, and malignant classes of Breast US Images dataset.

Figure 2 – Samples from the Breast US Images, utilized to assess the proposed method.



Benign Malignant

Source: Authors.

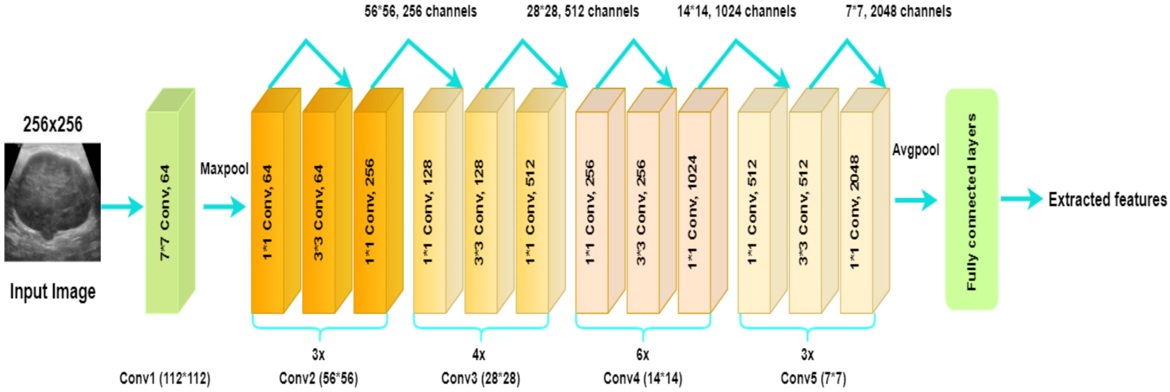
3.2 TRANSFER LEARNING-BASED FEATURE EXTRACTION

Transfer learning is the procedure of applying a pre-trained model that has been trained on one problem to another that is similar. Due to its prior experience with a similar issue, it has the benefit of requiring less training time. When it comes to image classification tasks, 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 models including ResNet50, MobileNetV2, DenseNet121, and Xception have been conducted to extract the BUSI's most significant features.

3.2.1 Modified Resnet50 network

It is a 50-layer deep convolutional neural network architecture, which firstly presented by (He, 2016). It consists of 48 Convolution layers, a MaxPool layer, and an Average Pool layer. ResNet50 is one of the most common ResNet versions with an input size of 256x256. In 2015, ResNet won the ImageNet challenge over other architectures and since then it has been used in various computer vision applications such as object detection, image segmentation, and image classification. The use of skip connections between layers (as shown in Figure 3) helps to reduce the number of parameters while also addressing the vanishing gradients problem associated with extremely deep CNNs (Boumaraf, 2021).

Figure 3 – The deep feature extractor ResNet50 architecture.

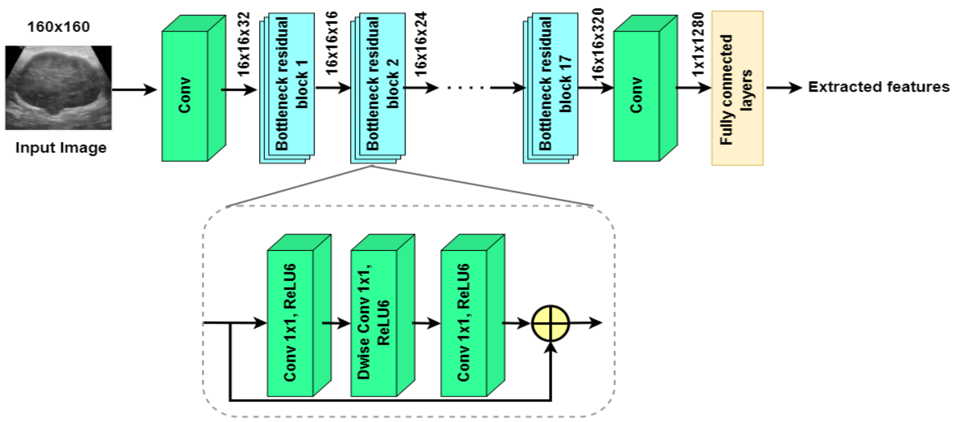


Source: Authors.

3.2.2 Modified Mobilenetv2 network

MobileNetV2 is a convolutional neural network architecture designed by Google for mobile and embedded vision applications (Majumdar, 2023), (Poyraz, 2022). It is an improved version of MobileNetV1, which was designed to be more efficient and faster than traditional computer vision models. MobileNetV2 uses depthwise separable convolutions, which are more computationally efficient than standard convolutions, to reduce the number of parameters and FLOPS (floating-point operations) required for inference. Additionally, MobileNetV2 adds a linear bottleneck layer to the end of each residual block (as seen in Figure 4), which helps reduce the amount of computation needed for inference (Sandler, 2018), (Sahin, 2022).

Figure 4 – The deep feature extractor MobileNetV2 architecture.

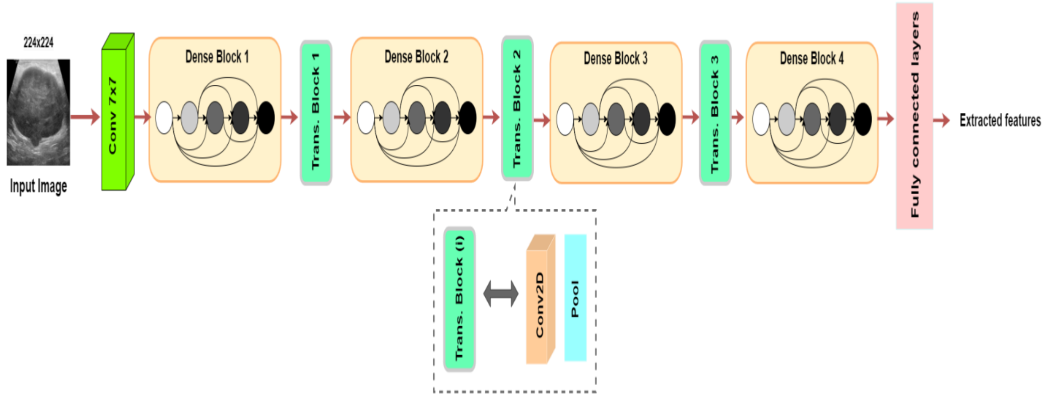


Source: Authors.

3.2.3 Modified Densenet121 network

DenseNet121 is a convolutional neural network architecture that was developed by Gao Huang *et al*. in 2017 (Huang, 2017). It is designed to improve upon traditional networks such as ResNet and Inception by introducing a new type of layer called a "dense block". The dense block allows information to flow more freely between different layers in the network, which improves performance by avoiding the vanishing gradients problem while significantly reducing the number of parameters required to learn at each layer (Boumaraf, 2021) (as shown in Figure 5).

Figure 5 – The deep feature extractor DenseNet121 architecture.

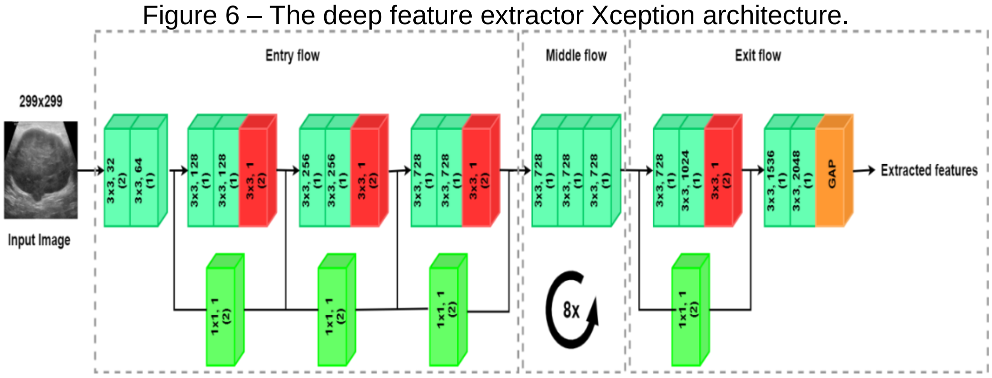


Source: Authors.

3.2.4 Modified Xception network

The Xception (i.e. Extreme Inception) model (Chollet, 2017) 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 (Shaheed, 2022). It has been used in a variety of fields in medical imaging with great success. The Xception feature extractor's architecture is described in Figure 6.

Figure 6 – The deep feature extractor Xception architecture.



Source: Authors.

3.3 MACHINE LEARNING CLASSIFIERS

The extracted features from various pre-trained models were passed through several commonly used classifiers such as Support Vector Machine (SVM), K Nearest Neigbour (KNN), XGBoost, and softmax for ultimate classification of breast cancer.

The Support Vector Machine (SVM) is a supervised machine learning technique proposed by (Cortes, 1995). It is used for classification tasks by creating a hyper-plane to separate two or more classes. We have implemented SVM as a classifier of all feature extractors with its default hyper-parameters.

The K Nearest Neighbors (KNN) (Kramer, 2013) algorithm, which is an effective machine learning classifier 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' similarity. The hyper-parameters of KNN were also set to their default values.

The eXtreme Gradient Boosting (XGBoost) algorithm, proposed by (Chen, 2016), as a peak performance classifier. XGBoost combines multiple weak trees with low performance rates to create a strong one. All hyper-parameters were set to their default values.

The last layer in each pre-trained model, which is the classifier, was modified by changing its number of neurons according to the data targets. In this case, Softmax was used with two units corresponding to the number of labels in the dataset.

4 RESULT & DISCUSSION

In order to accurately assess the performance of the proposed method, numerous experiments have been performed to assess the effectiveness by analyzing the performance of different pre-trained CNNs with different classifiers to select the best classifier with the best pre-trained model regarding to their performance. For this, several commonly used evaluation criteria have been implemented.

4.1 PERFORMANCE EVALUATION

The confusion matrix (cm) is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data samples for which the true values are known. It allows the visualization of the performance of an algorithm. Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class (or vice versa) (Aina, 2021), (Han, 2022). Different metrics such as Accuracy, Precision, and F1-score were calculated based on the cm for performance analysis (Grandini, 2022). The Mathematical Formulas of these criteria are presented in Table 1.

Table 1 – The evaluation metrics.

Evaluation criteria	Mathematical Formula	Description
Accuracy (Acc)	$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)}$	TP (True Positive): The label's actual value is True as well as the predicted value. TN (True Negative): The label's actual value is False as well as the predicted value. 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.
Precision (Pre)	$Pre = \frac{TP}{(TP+FP)}$	
F1-score (F1)	$F1-score = \frac{2*TP}{(2*TP+FN+FP)}$	

Source: Authors.

4.2 PERFORMANCE ASSESSMENT OF DEEP MODIFIED TRANSFER LEARNING-BASED CNN NETWORKS

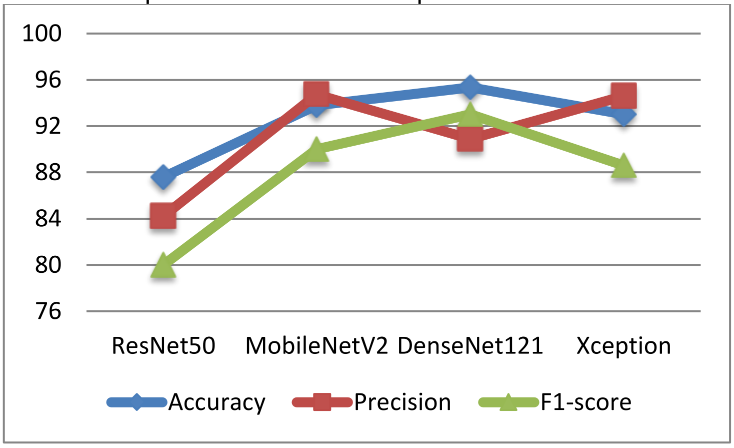
As demonstrated in Table 2, all pre-trained CNN models experienced a significant improvement when using the softmax classifier. This latter attained the highest accuracy of 95.34% with Densenet121 compared to other CNNs. The performance concerning various feature extractors with the softmax classifier is depicted in Figure 7.

Table 2 – Performance evaluation of different deep CNN networks with various classifiers.

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

Source: Authors.

Figure 7 – Performance comparison of different deep CNN networks with the softmax classifier.



Source: Authors.

5 COMPARISON WITH THE STATE-OF-THE-ART METHODS

In this section, we have compared our proposed method to several other existing studies that used the same protocol and performance metrics. Table 3 shows that our method outperformed all of these researches with an accuracy of 95.34%. It is worth noting that all these researches were conducted between 2020 and 2024.

Table 3 – Accuracy-based comparison of the proposed method with existing studies.

Refs	Task	Dataset	Method	Accuracy (%)
(Byra, 2021)	Binary Classification	BUSI	TL-based deep representation scaling (DRS)	91.5
(Inan, 2022)	Multi-Classification	BUSI	ResNet50	73.72
(Qi, 2022)	Binary Classification	BUSI	DeepCls	94.51
Ours	**Binary Classification**	**BUSI**	**Deep Modified DenseNet121 Network**	**95.34**

Source: Authors.

6 CONCLUSION

This study proposes a method using deep-modified transfer learning-based CNN networks for early breast cancer detection and treatment of breast cancer as a feasible method. First, the BUSI images are inputted into feature extractors to capture their relevant features. Subsequently, the extracted features are accurately classified as benign or malignant using high-performance classifiers such as SVM, KNN, XGBoost, and softmax. Using deep modified Densenet121 with softmax classifier outperforms other CNN networks and existing detection techniques, achieving 95.34% (accuracy), 90.90% (precision), and 93.02% (F1-score). The research outcomes offer substantial societal and academic benefits by facilitating early cancer detection and advancing research in medical imaging and diagnostics. However, the study has certain limitations, including the use of a specific dataset and the necessity for real-world testing to ensure practical viability. Future plans include integrating the method with other diagnostic modalities and exploring applications beyond breast cancer to enhance diagnostic capabilities. In addition, collaboration among stakeholders is essential for translating these findings into impactful medical solutions.

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