Comparative Analysis of Artificial Intelligence-Based Algorithms for Early Detection of Breast Cancer

Pedro Narciso Delgado Chávez
Universidad Técnica de Manabí
pdelgado4456@utm.edu.ec
Portoviejo, Ecuador

Roberth Abel Alcívar Cevallos
Universidad Técnica de Manabí
roberth.alcivar@utm.edu.ec
Portoviejo, Ecuador

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ABSTRACT

Breast cancer is one of the leading causes of mortality among women worldwide, representing a major public health problem. Early detection is crucial for increasing survival rates, since establishing a timely diagnosis and applying the appropriate treatment can help stop the disease in its early stages. In this context, the use of algorithms based on artificial intelligence has become a highly relevant tool in the field of early diagnosis, particularly within medical oncology. Several algorithms have demonstrated great potential in accurately classifying medical images, including Support Vector Machines (SVM), Random Forests, Multilayer Perceptrons (MLP), and Convolutional Neural Networks (CNN). This approach enables a more detailed and reliable analysis of medical imaging studies (mammograms, ultrasounds, computed tomography, and magnetic resonance imaging), facilitating the early detection of malignant lesions and reducing diagnostic errors. The main objective of this research was to conduct a comparative analysis of artificial intelligence-based algorithms and evaluate, through metrics such as accuracy, sensitivity, specificity, F1-score, and the area under the curve (AUC), which algorithm performs best in the early detection of the disease. Consequently, the integration of artificial intelligence algorithms into clinical decision support systems contributes significantly to improving medical decision-making, ensuring that treatments are more appropriate, and providing a better quality of life for patients diagnosed with the disease.

Keywords: Artificial Intelligence, Breast Cancer, Ultrasound, Machine Learning, Deep Learning.

Análisis comparativo de algoritmos basados en inteligencia artificial para la detección temprana del cáncer de mama

Resumen

El cáncer de mama constituye una de las principales causas de mortalidad en mujeres a nivel mundial, representando un gran problema de salud pública. La detección temprana resulta determinante para incrementar las tasas de supervivencia, ya que al establecer un diagnóstico oportuno y poder aplicar el tratamiento adecuado que favorezca aparar la enfermedad en sus fases tempranas (estadio).Este contexto, de emplear los algoritmos basados en inteligencia artificial se ha convertido en una herramienta de gran relevancia en el campo del diagnóstico temprano en este caso en la rama médica de la oncología. Diversos algoritmos han demostrado un gran potencial en la precisión, en la clasificación de la imágenes médicas entre ellos se tiene la Máquina de vectores de soporte (SVM), Bosques aleatorios(Random Forest) ,Perceptron multicapa (MLP) y Redes neuronales convolucionales(CNN).Este enfoque permite realizar un análisis más detallado y confiable de estudios de imágenes médicas (mamografías, ecografías, tomografías y resonancias magnéticas) dando facilidad para la detección temprana de lesiones malignas y reducir diagnósticos erróneos. El objetivo fundamental de la investigación fue realizar una comparativa de los algoritmos basados en inteligencia artificial y medir a través de las métricas como la precisión ,sensibilidad, especificidad ,f1-score y el área bajo la curva(AUC), cual es el algoritmo con mejor rendimiento para la detección temprana de la enfermedad . En consecuencia, la integración de algoritmos basados en inteligencia artificial en los sistemas de apoyo clínico contribuye de manera significativa a mejorar las decisiones médicas y que el tratamiento sea el más adecuado y se brinde una mejor calidad de vida de las pacientes diagnosticadas con la enfermedad.

Palabras clave: Inteligencia Artificial, Cáncer de mama, Ultrasonido, Aprendizaje Automático, Aprendizaje Profundo.

1. Introduction

Breast cancer is one of the diseases with the highest mortality rate among women worldwide and represents one of the leading causes of death in the female population. Early detection of breast cancer is essential to improve the chances of effective treatment and to increase survival rates. However, early identification of the disease has its limitations due to the variability in the presentation of lesions in ultrasound images. (Sorlien Asne Holen, 2024)

Artificial intelligence is a branch of computer science that encompasses concepts related to learning, logical reasoning, and autonomous decision making. It focuses on the design and development of computational systems capable of learning from data, reasoning logically, and self-correcting their processes, thereby enabling the simulation of aspects of human intelligence. (Escalante González , 2023)

In recent years, artificial intelligence (AI) has shown significant progress in the field of medicine, particularly in the interpretation of medical images. The advances in Artificial Intelligence (AI) are rapid, comprehensive, and increasingly effective. There is controversy regarding the acceptance of computerized breast cancer detection, with patient trust on one hand and the competitiveness of the algorithm on the part of the medical community. For this reason, algorithms such as Support Vector Machines (SVM), Random Forest, Multilayer Perceptron (MLP), and Convolutional Neural Networks (CNN) have been employed. (Rajasekaran Subramanian Dr, 2021)

The main objective of the study is to identify which of the evaluated algorithms offers the best performance in the early detection of breast cancer. For the comparison, accuracy, sensitivity, specificity, F1 score, and area under the curve (AUC) were considered as reference metrics, using a set of ultrasound images. The evaluation of the algorithms allows for the identification of their strengths and weaknesses, which provides relevant information for their application in clinical decision support systems. (Xhako

Dafina, 2024)

2. Methodology

This research was supported by prior theoretical and practical knowledge previously established in the fields of machine learning and deep learning. The study is applied in nature, as it sought to solve a practical problem by evaluating machine learning and deep learning algorithms, addressing a real-world issue. It is also experimental, since simulations and tests were conducted on artificial intelligence–based algorithms, allowing the observation of results that, from the outset, show expected results. (Zou Sheng, 2024)

2.1 Methods

This article employed three methods: quantitative, qualitative, and comparative. The quantitative approach used key metrics such as accuracy, sensitivity, specificity, and the area under the curve (AUC) to evaluate the algorithms' performance in detecting patterns in medical images(mammograms, ultrasound, and magnetic resonance imaging). (Ragab Dina, 2019)

Within the quantitative approach, the variables normal, benign, and malignant were used to evaluate the effectiveness of artificial intelligence–based algorithms. The use of these variables allowed for better data adjustment, reducing image quality loss and minimizing the likelihood of less efficient outcomes, such as false positives and true negatives. The main objective of the testing phase was to ensure that the results were efficient, thereby increasing the reliability of the algorithms.

The comparative method made it possible to determine which algorithm offers the best performance in the early detection of breast cancer, considering aspects such as diagnostic accuracy, training time, and overall performance. By applying the three methods, each detail was analyzed and carefully considered in the metrics and variables to obtain reliable results.

2.2 Information Collection Techniques

Among the techniques employed in this research, an exhaustive literature review was conducted on academic-scientific articles, academic journals, and systematic reviews concerning artificial intelligence–based algorithms for breast cancer detection, using academic databases such as Scopus, IEEE Xplore, ResearchGate, Google Scholar, Science Direct, and PubMed.

2.3 Tools and Resources.

As part of the development and modeling tools, the artificial intelligence algorithms used in this research were designed, trained, tested, and compared. Through these stages of the work, improvements in each of the algorithms could be observed.

2.4 Technological Equipment

A computer system was used with the following hardware specifications: an 11th-generation Intel Core i5 processor at 4.2 GHz, 8 GB of RAM, a 521 GB solid-state drive, and an NVIDIA TX 9800 graphics card. At the software level, Windows 11 Single Language was employed, along with Google Collaboration, a cloud-based environment running Python 3.10 and providing GPU (Graphics Processing Unit) support for image data processing. The operating system (Windows 11) was complemented with Keras 3.0 as the standard library for image processing tasks and Tensor Flow version 2.13, which operates in conjunction with Python.

2.5 Phases of the Research Work

2.5.1 Planning and Data Collection

An exhaustive literature review was conducted on artificial intelligence–based algorithms for breast cancer detection. Additionally, the dataset for the research was sourced from recognized repositories such as Kaggle, among others.

2.5.2 Data Preprocessing

The dataset was collected and analyzed, with particular attention given to its structure in order to determine the variables most relevant for this study. It consisted of clinical images (mammograms and ultrasounds). For the purposes of this research, ultrasound images were selected, and the Support Vector Machine (SVM) algorithm was initially applied. Key features were extracted to obtain meaningful data, which were then processed and refined to ensure consistency and reliability.

The Breast Ultrasound Images (BUSI) dataset was used, comprising 1,578 images in total: 266 classified as normal, 891 benign, and 421 malignant. The quality and suitability of the images for algorithmic processing were carefully reviewed. When necessary, adjustments were made to attributes such as brightness, contrast, weight, and dimensions, which facilitated the preprocessing stage and improved the dataset's usability. Once this process was completed, the dataset was prepared for the training and evaluation phases of the selected algorithms. To further improve image quality and achieve more optimal results, additional preprocessing techniques were applied using Python's OpenCV (cv2) library, in combination with the CLAHE

(Contrast Limited Adaptive Histogram Equalization) method, implemented locally.

The data were divided into 70% for training, 15% for validation, and 15% for testing. The hyperparameters were configured as follows: for SVM, the RBF kernel function; for Random Forest, 100 decision trees with a fixed seed of 42; for the Multilayer Perceptron (MLP), three hidden layers (128, 64, 32); and for the Convolutional Neural Networks (CNN), three convolutional layers with ReLU activation, 10 epochs, and the Adam optimizer.In addition, k-fold cross-validation was performed, with the number of folds ranging between 5 and 10. After these procedures, the models were trained and evaluated, and their performance metrics were compared to identify the most effective algorithm.

It should be noted that the BUSI dataset is organized into three subdirectories: normal, benign, and malignant, which served as the basis for classification into these three categories throughout the study. In the appendix, the raw images and the processed images are presented.

2.5.3 Algorithm Training and Evaluation

In this phase of the research, where the algorithms were trained and evaluated, the Breast Ultrasound Images Dataset (BUSI) was selected, which contains 1,578 images distributed across the categories normal, benign, and malignant. Equal conditions were granted to all algorithms during training and evaluation, as they were tested on the same dataset. The Support Vector Machine (SVM) algorithm was evaluated first, since it directly extracts relevant features from medical images (such as ultrasound and mammograms), including dimension, texture, weight, and shape, and adapts them to work more efficiently.

Next, the Random Forest algorithm was evaluated, which bases its operation on making the best decision by working with multiple decision trees. Similar to SVM, it transforms these features into a feature vector of the images and evaluates them as a classifier. Each decision tree casts a vote for a class, and the final result is determined either by majority voting or by averaging the outputs of the trees. Subsequently, the Multilayer Perceptron (MLP) algorithm was assessed.

This artificial neural network is composed of layers of nodes (neurons). When evaluated with medical images, it processes the data through its layers, producing as output a class value: normal, benign, or malignant. As the data passes through the iterations of its hidden layers, the algorithm ultimately selects the class determined by its programmed logic. Finally, the Convolutional Neural Network (CNN) algorithm was evaluated. CNNs operate directly on images by automatically detecting relevant spatial patterns through the use of convolutions.

This study constitutes a comparative analysis of the aforementioned algorithms; therefore, their performance was measured using quality metrics such as accuracy, sensitivity, specificity, F1-score, and area under the curve (AUC), in order to determine which algorithm performs best in the processing of medical images (ultrasound).

3. Results and Discussion

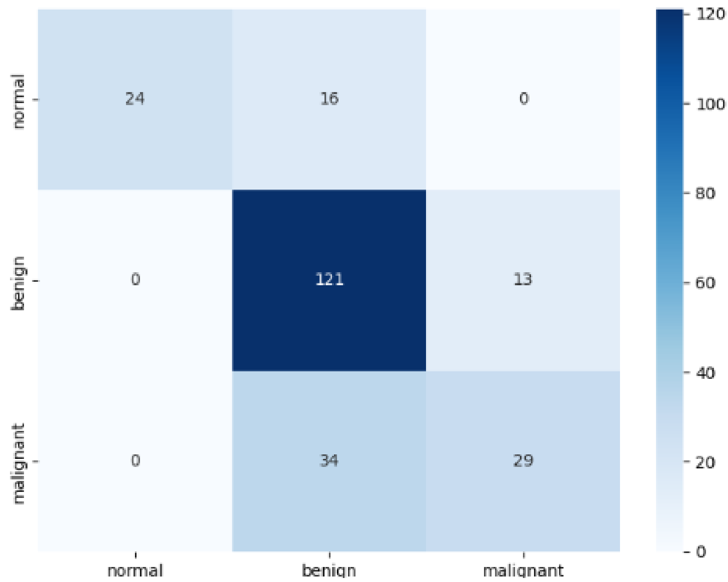
3.1 Results

The results obtained from the comparative analysis of the algorithms employed in this research for the early detection of breast cancer were derived using the Breast Ultrasound Images (BUSI) dataset, which contains a total of 1578 images (266 normal, 891 benign, and 421 malignant).Each algorithm was trained and evaluated, and confusion matrices were generated along with the specified metrics, including accuracy, sensitivity (recall), specificity, F1 score, and area under the curve (AUC).

The simplified confusion matrices for each algorithm are presented below, based on the medical images dataset, with 15% of the data reserved for validation, as shown in Figures 1, 2, 3, and 4.

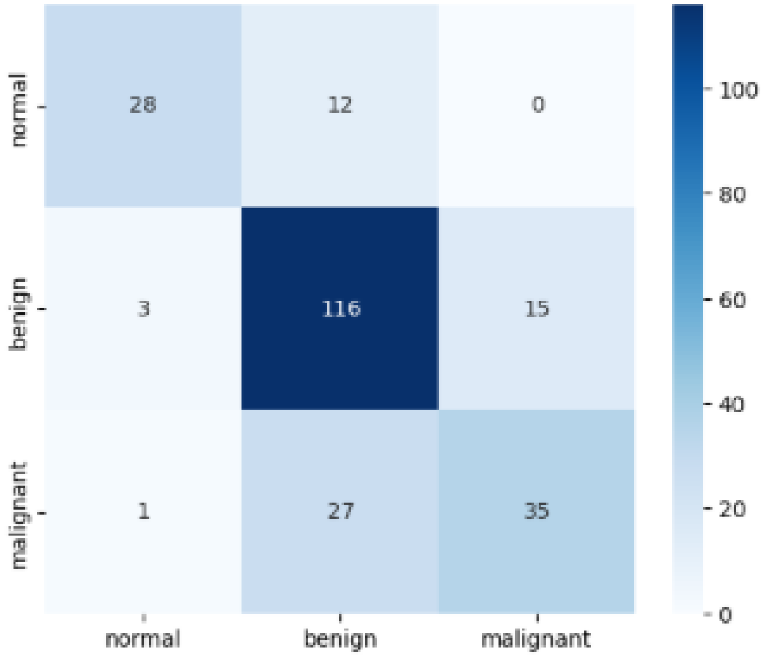
Additionally, a comparative data table and a graph of errors in accuracy and loss experienced by the algorithms are shown in Table 3 and Figure 11:

Figure 1. Confusion Matrix of the Support Vector Machine (SVM) Algorithm



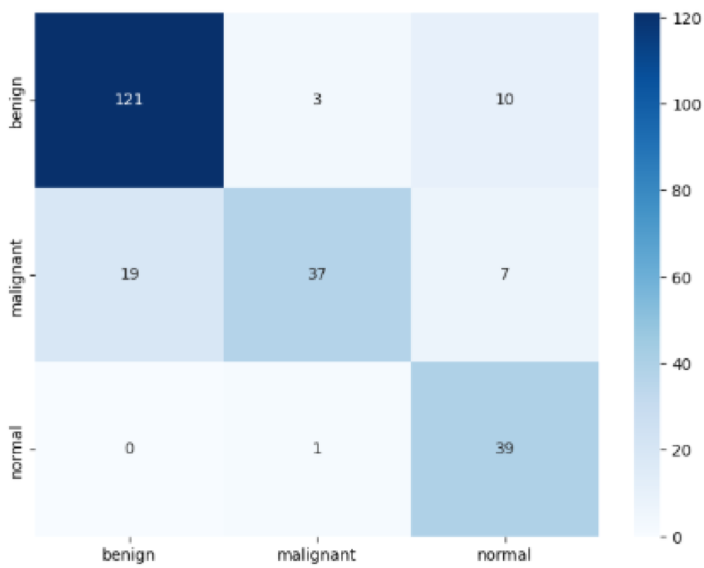
Note: Pedro Delgado (2025).

Figure 2. Confusion Matrix of the Random Forest Algorithm



Note: Pedro Delgado (2025).

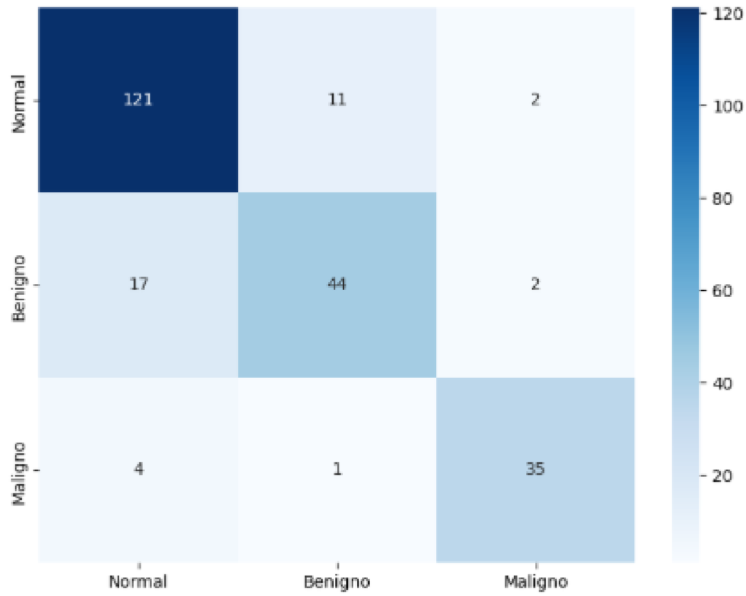
Figure 3. Confusion Matrix of the Multilayer Perceptron (MLP) Algorithm



Note: Pedro Delgado (2025).

Figure 4. Confusion Matrix of the Convolutional Neural Networks (CNN)

Algorithm.



Note: Delgado Pedro (2025).

3.2 Discussion

This section of the article presents a comparative table of the algorithms evaluated in terms of efficiency and performance, along with the metrics of accuracy, sensitivity (recall), F1 score, and area under the curve (AUC).An additional column was included to report the training time, and a graph was provided with the corresponding values obtained in the study.

The results show that Convolutional Neural Networks (CNN) achieved the best overall performance (accuracy of 88%, AUC = 0.92), hich has been observed in previous studies that highlight their effectiveness in the classification of medical images. The Multilayer Perceptron (MLP) achieved a sensitivity of 86%, which is a good result but could have limitations when computational resources are low.

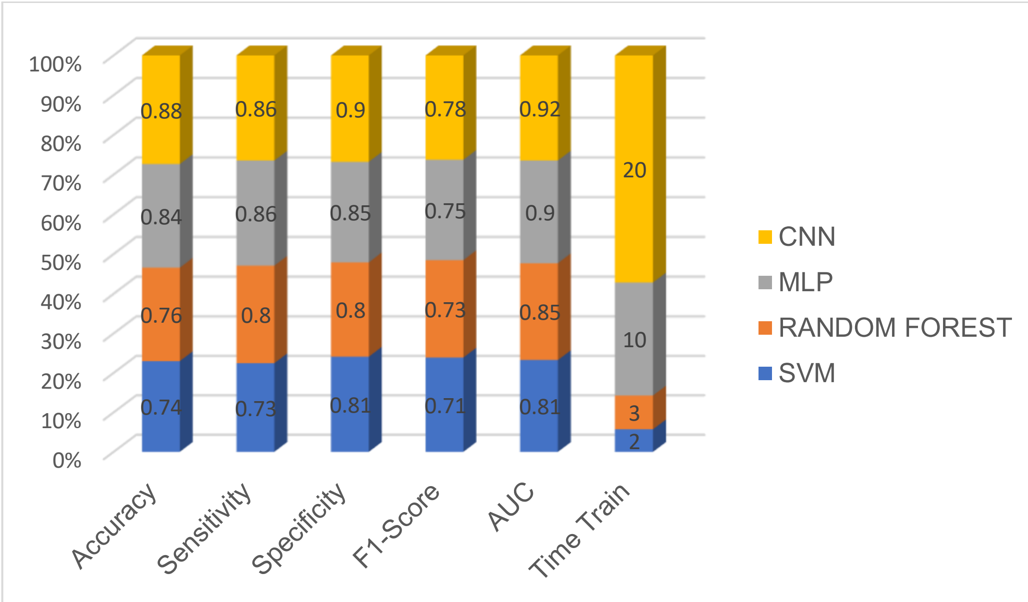
The Support Vector Machine (SVM) and Random Forest algorithms showed intermediate performance, with accuracies close to 74-76% and an AUC of 0.81 for SVM and 0.85 for Random Forest. These findings suggest that the algorithms should be adapted to clinical needs: CNN for greater accuracy, MLP when the minimization of false negatives is a priority, and SVM or Random Forest when a balance between performance and computational simplicity is required. The following table and graph illustrate the results described in this discussion.

Table 1. Comparison of metric values and the respective algorithms used

Algorithm	Accuracy	Sensitivity (Recall)	Specificity	F1-Score	AUC	Training Time (min)
SVM	0.74	0.73	0.81	0.71	0.81	2
RF	0.76	0.80	0.80	0.73	0.85	3
MLP	0.84	0.86	0.85	0.75	0.90	10
CNNs	0.88	0.86	0.90	0.78	0.92	20

Note: Pedro Delgado (2025).

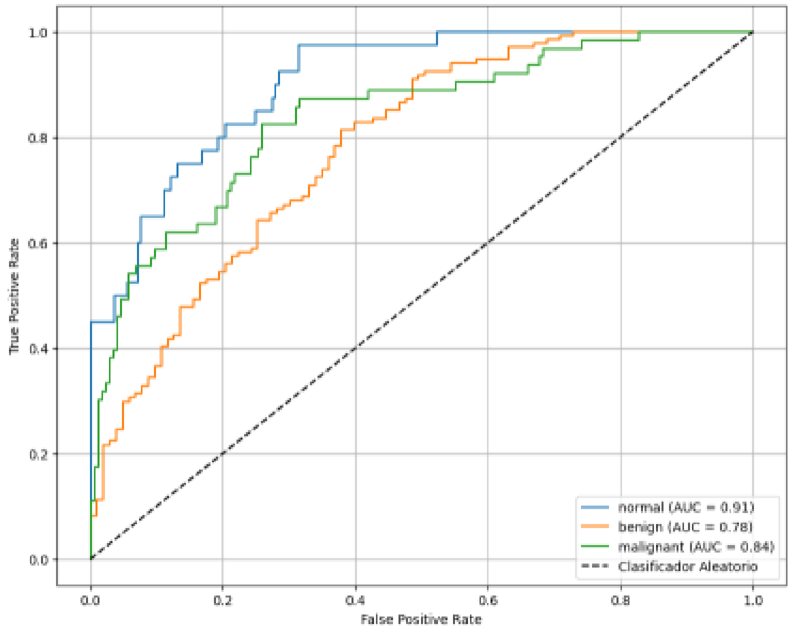
Figure 5. Accuracy, Sensitivity, Specificity, F1-Score, AUC, and Training Time Metrics



Note: Pedro Delgado (2025).

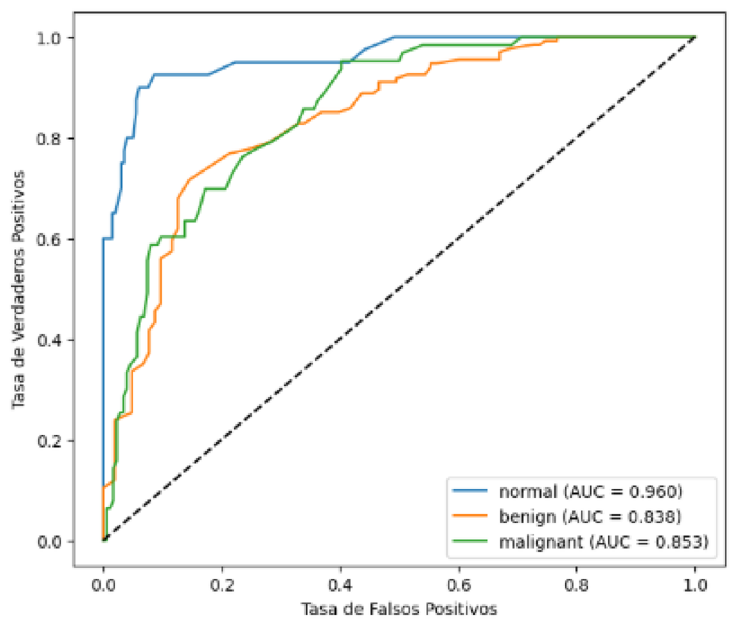
In the discussion section, the area under the curve (AUC) graphs are presented to provide a clearer view of how the results of each evaluated algorithm were validated.

Figure 6. Support Vector Machine (SVM) Algorithm – AUC Curve



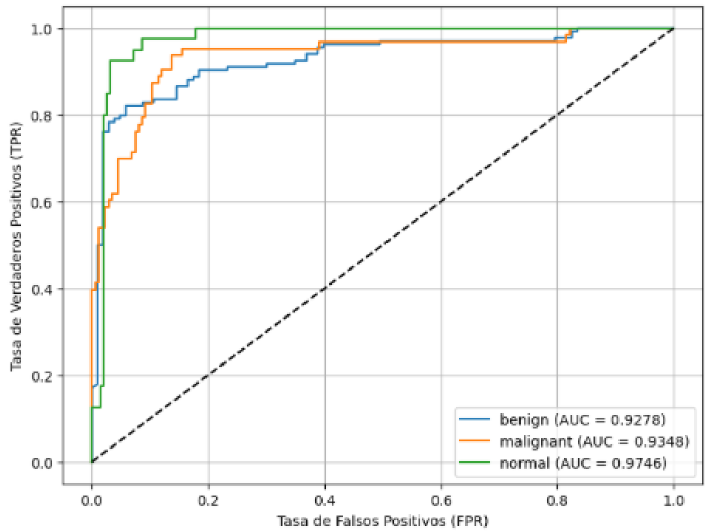
Note: Pedro Delgado (2025).

Figure 7. Random Forest Algorithm – AUC Curve



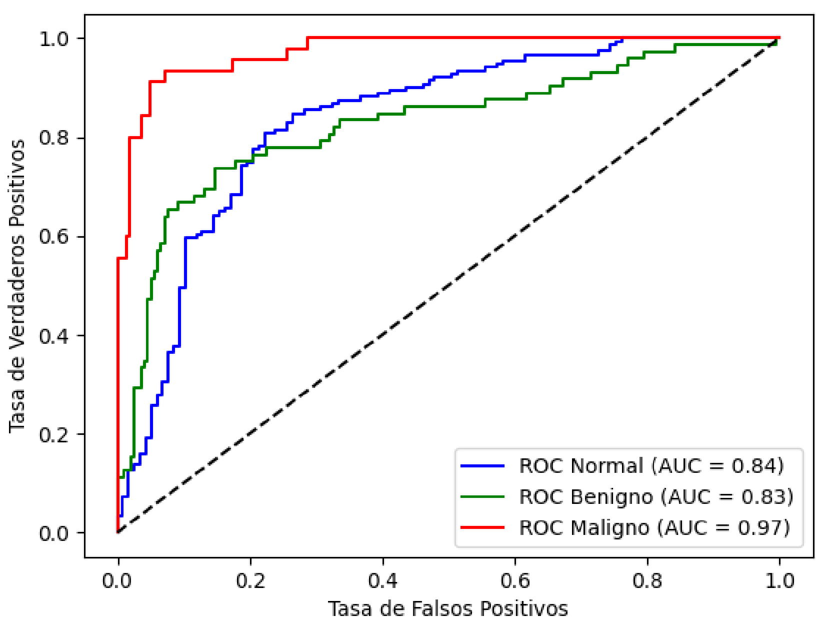
Note: Pedro Delgado (2025).

Figure 8. Multilayer Perceptron (MLP) – AUC Curve



Note: Pedro Delgado (2025).

Figure 9. Convolutional Neural Networks (CNN) Algorithm – AUC Curve



Note: Pedro Delgado (2025).

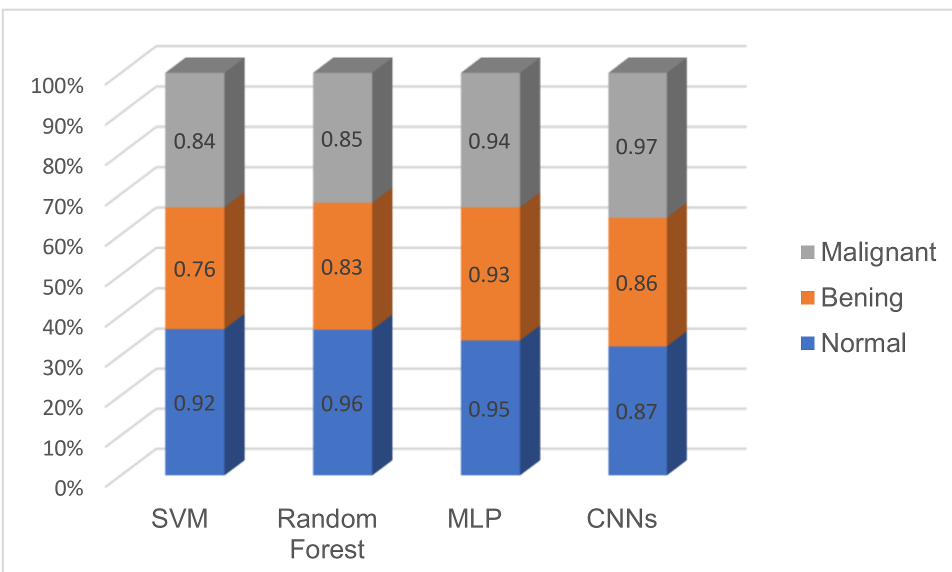
In the table two (2), shows the values obtained for each class: normal, benign, and malignant, after the evaluation of each algorithm used in the research:

Table 2. Comparison of Algorithms Based on the Area under the Curve (AUC) Metric.

Algorithms	Normal	Bening	Malignant
SVM	0.92	0.76	0.84
Random Forest	0.96	0.83	0.85
MLP	0.95	0.93	0.94
CNNs	0.87	0.86	0.97

Note: Pedro Delgado (2025).

Figure 10. Bar Chart of the Algorithms Compared Using the Area Under the Curve (AUC) Metric.



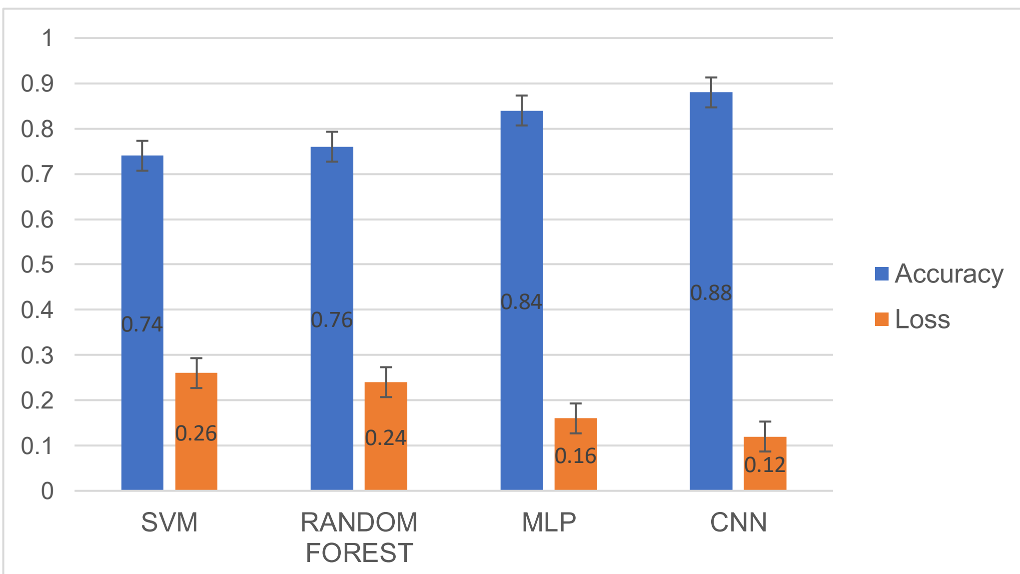
Note: Pedro Delgado (2025).

Table 3. The accuracy and loss values are shown for each of the algorithms.

Algorithms	Accuracy	Loss
SVM	0.74	0.26
RANDOM FOREST	0.76	0.24
MLP	0.84	0.16
CNN	0.88	0.12

Note: Pedro Delgado (2025).

Figure 11. Graph of the accuracy and losses in the evaluated algorithms.



Note: Pedro Delgado (2025).

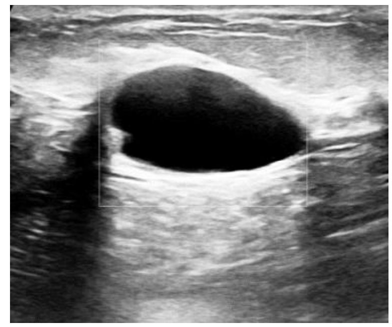
5. - Conclusions

A 2024 study by Zou et al, on breast cancer prediction, which utilized various algorithms, including the Support Vector Machine (SVM) and Random Forest (RF), demonstrated that these algorithms perform well with binary datasets like the Wisconsin dataset. In contrast, when applied to the ultrasound breast image dataset used in the comparative analysis article on AI-based algorithms for early breast cancer detection, SVM and RF achieved acceptable, yet lower, accuracy scores of 0.74 and 0.76, respectively. This finding suggests that while these algorithms may not be optimally suited for direct medical image analysis, they can still be effectively employed on datasets with similar underlying features.

Furthermore, other studies have highlighted that the Multilayer Perceptron (MLP) and Convolutional Neural Networks (CNNs) are powerful tools in the field of medical image diagnostics. In this specific study, they yielded superior results, with an accuracy of 0.84 for MLP and 0.88 for CNNs.

Beyond the standard accuracy metric, another critical performance measure is the Area under the Curve (AUC-ROC). This metric, which evaluates how well the algorithm classifies each category within the medical image dataset, also showed strong results. CNNs demonstrated exceptional capability, leading with an AUC of 0.97 for the malignant class, 0.86 for the benign class, and 0.87 for the normal class. Based on these comparative values and metrics, it can be concluded that Convolutional Neural Networks (CNNs) are the superior algorithm when compared to SVM, Random Forest, and MLP for this specific task of early breast cancer detection using medical images.

Appendix



A **B**

In the following figures, we present a benign-class image prior to preprocessing (Figure A). In contrast, Figure B shows the same image after undergoing preprocessing using the CLAHE technique (Contrast Limited Adaptive Histogram Equalization).

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