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Breast tumor classification using adam and optuna model optimization based on CNN architecture

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ABSTRACT

Breast cancer presents a significant challenge due to its complexity and the urgency of the intervention required to prevent metastasis and potential fatality. This article highlights the innovative application of Convolutional Neural Networks (CNN) in breast tumor classification, marking substantial progress in the field. The key to this advancement is the collaboration among medical professionals, scientists, and artificial intelligence experts, which maximizes the potential of technology. The research involved three phases of training with varying proportions of training data. The first training phase achieved the highest accuracy rate of 99.72%, with an average accuracy of 99.05% in all three phases. Metrics such as precision, recall, and F1 score were also highly satisfactory, underscoring the model's efficacy in accurately classifying breast tumors. Future research aims to develop more complex and precise predictive models by incorporating larger and more representative datasets. This progression promises to improve understanding, prevention, and management of breast cancer, offering hope for significant advances in 2024 and beyond.

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1. INTRODUCTION

Breast cancer in the world, according to the latest data summarized every 5 years and released by the World Health Organization (WHO), is a challenge that continues to be alarming in the field of global health. Breast cancer is a disease of complexity, characterized by the uncontrolled growth of breast cells, which, if left untreated can result in the spread of cancer to various parts of the body and have potentially fatal consequences [1]. In 2020, the statistics provided by the WHO were astonishing, with up to 2.3 million women worldwide receiving a diagnosis of breast cancer and more than half a million deaths caused by this disease [2]. Even after diagnosis, the challenges of breast cancer persist. At the end of 2020, approximately 7.8 million women had a history of breast cancer in the past five years [2], [3]. Breast cancer has reached the status of one of the most common cancers faced by women worldwide, and despite improvements in survival rates since the 1990s, thanks to early detection programs and the development of more effective medical therapies, this challenge remains a focus of attention. major in the world of health in 2023 [4].

When solving the problem of potential breast tumor classification using convolutional neural networks (CNN) and model optimization with Optuna and Adam optimizer, several solution steps can be taken. Initially, the collection of information and data sets involved the collection of high-quality medical data that contain relevant breast radiology images, the guarantee of their authenticity, and compiling them into a data set ready for model training and testing of the models. Subsequently, data pre-processing, which includes image normalization, noise removal, and handling missing or incomplete data, improves data quality and final model results. Tumor segmentation employs appropriate techniques to help CNN models isolate relevant areas, enhancing classification accuracy. The next step involves developing and training a suitable CNN model using the prepared dataset, a crucial phase in the classification process. Finally, once the CNN model is generated and tested, it can be applied to potential cases of breast tumor detection cases, classifying radiological images to identify possible tumors. The results of this model provide valuable information for further diagnosis and treatment.

Table 1. State of the art

Researcher	Year	Method and novelty	Result (accuracy)
Srikantamurthy, Rallabandi, et al. [5]	2023	CNN-LSTM built with 3 different optimizers (Adam, SGD, and RMSProp)	92,5% - 99%
Samee, Atteia, et al. [6]	2022	Addressing FDC using Specific Transfer Learning with Experimental Architectures (AlexNet, VGG, and GoogleNet)	98,50%
Alqahtani, Mandawkar, et al. [7]	2022	Deep Learning CNNs	88,87%
Pathan, Alam, et al. [8]	2022	Multi-Headed Convolutional Neural Network Model	92.31%
Mohapatra, Muduly, et al. [9]	2022	DCNN with AlexNet, VGG16, and ResNet50 architecture models	61% - 65%

Several researches, as shown in Table 1 are relevant with our proposed method. The research by Srikantamurthy, Rallabandi et al. (2023) compared the proposed CNN-LSTM hybrid model with existing CNN models such as VGG-16, ResNet50, and Inception in the classification of breast histopathology images. All models were built using three different optimizers, namely the adaptive moment estimator (Adam), the root mean square propagation (RMSProp), and the stochastic gradient descent (SGD), with variations in the number of epochs. The results show that the Adam optimizer is the best with maximum accuracy and minimal model loss for training and validation data. The proposed CNN-LSTM hybrid model demonstrated the highest overall precision of 99% for binary classification of benign and malignant cancers, as well as 92.5% for multiclass classification of benign and malignant cancer subtypes [5].

Breast cancer research by Samee, Atteia, and others (2022) aims to overcome the "Feature Dimensionality Curse" (FDC) problem in deep features derived from transfer learning pre-trained CNNs. This problem arises due to the high dimensionality of the extracted deep features compared to the limited number of medical data samples. They proposed a deep learning-based feature selection framework combined with a univariate paradigm. Deep learning models such as AlexNet, VGG, and GoogleNet are used to extract features from INbreast mammograms, while univariate strategies help overcome high-dimensional and multicollinearity problems. The optimal features produced through the univariate approach have good capabilities in the training of classification models with accuracy reaching 98.50%, sensitivity of 98.06%, specificity of 98.99%, and precision of 98.98% [6].

Breast cancer research by Alqahtani, Mandawkar, and others (2022) proposed a deep learning-based classification strategy to overcome the challenges of automatic categorization of breast cancer pathology images. This model uses channel recalibration to increase classification accuracy utilizing the learned channel weights. Experimental results show that this model is capable of classifying breast pathology images with an accuracy of approximately 888.87 percent, including images taken at various magnification levels, which can improve efficiency in the diagnosis of breast cancer [7].

Breast cancer research by Pathan, Alam, and others (2022) uses artificial intelligence to detect breast cancer by analyzing ultrasound images from the Breast Ultrasound Image (BUSI) data set. The results show that the proposed system is effective, with testing accuracy reaching 92.31% after using multiheaded CNN with two different types of input data, namely the original image and the masked image. This can help reduce human error in the breast cancer diagnosis process. In addition, this research also presents a web interface so that this model can be used by non-technical individuals [8].

Research by Mohapatra, Muduly and others (2022) shows that deep learning approaches in breast cancer detection have attracted great interest, especially because the precision of conventional CAD-based systems appears to be inadequate. In this investigation, CNN, as a deep learning approach, was used to classify mammogram images into three categories: benign, cancerous, or normal. The performance of several CNN architectures such as AlexNet, VGG16, and ResNet50 was evaluated, both by training from scratch and by using transfer learning using pre-trained weights. The use of the mini-DDSM dataset for training and testing overcomes the limitations of available medical samples, and a data augmentation process is used to overcome the overfitting problem. As a result, AlexNet achieved an accuracy of 65%, while VGG16 and ResNet50 achieved an accuracy of 65% and 61% when transfer learning was applied. VGG16 performs worse when trained from scratch, while AlexNet outperforms the others. VGG16 and ResNet50 show good performance when transfer learning is used [9].

In the global effort to overcome breast cancer, collaboration extends beyond medicine and health, encompassing technology and artificial intelligence. An innovative approach involves applying computational neural networks (CNN) for the classification of potential breast tumors. Maximizing the potential of this technology to improve understanding, prevention, and treatment of breast cancer in 2023 and beyond requires collaboration between medical professionals, the scientific community, and AI experts. The central research question is: "How can we more effectively combine artificial intelligence technologies, such as CNN, with optimization approaches like Optuna and the Adam optimizer for early detection of breast cancer?" Addressing this question requires cooperation across diverse fields, including medical science, computer science, and artificial intelligence.

2. METHOD

Dataset Collection

Data collection in this research was carried out by accessing the dataset available on the Kaggle platform. This data set consists of MRI images with a size of 256 x 256 pixels, and in total there are 54,676 images as visualized in the sample in Figure 1. The data collection process involves downloading Kaggle datasets, which will then be used in research for analysis, model training, and evaluation in the context of classification or other relevant tasks. The Kaggle data available provides a strong foundation for this research, allowing in-depth analysis and significant results in the context of detection or classification that may be the focus of this research [10].

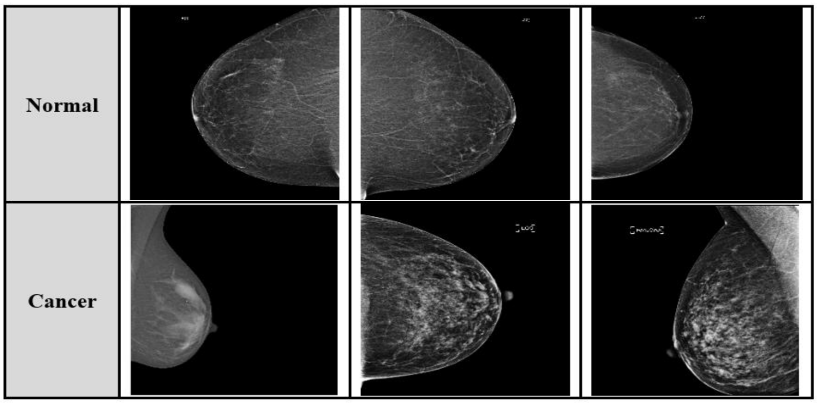


Figure 1. Sample of dataset

Preprocessing

The preprocessing process in this research is an important stage in data preparation before being involved in further analysis. MRI images measuring 256 x 256 pixels from the Kaggle dataset must go through a series of preprocessing steps to ensure optimal data quality and consistency. This includes normalization of image intensity to remove intensity variability between images, as well as removal of any noise that may be present [11]. In addition to that, the preprocessing process also includes handling missing or incomplete data, such as filling in missing values if necessary [10]. The preprocessing stage can be seen in Figure 2.

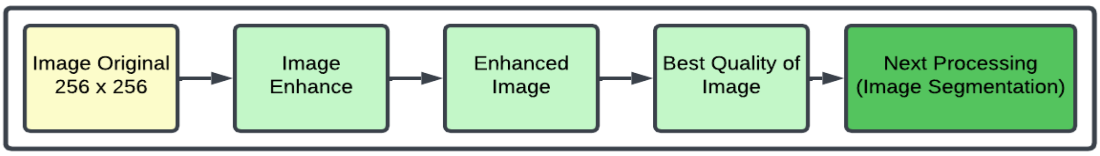


Figure 2. Pre-processing stages

Image Segmentation

Segmentation is a critical stage in this research, which aims to identify and isolate relevant areas in magnetic resonance images [11]. Using advanced segmentation techniques, we can isolate parts of the image that depict potential tumors or specific areas of research focus. This segmentation process will help limit attention to relevant areas, which can then be used in further analysis, such as detection or classification [12]. By having accurate segmentation results, we can improve efficiency and accuracy in this research, which will contribute to a better understanding of magnetic resonance images in the context of breast health. The image segmentation stage can be seen in Figure 3.

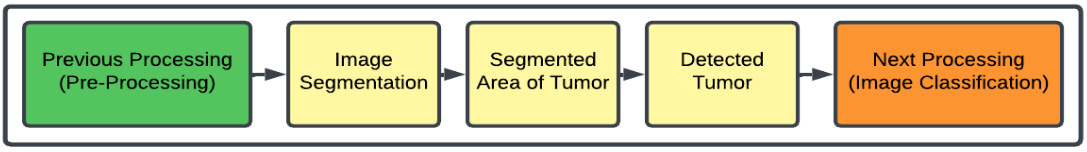


Figure 3. Segmentation stages

Proposed Method Based on Convolutional Neural Network

CNN is a type of artificial neural network architecture that has become very important in image processing and pattern recognition [13]. CNNs are specifically designed to handle data in the form of images or grid data, such as medical images [14], and have produced extraordinary advances in various fields, including classification tasks [15]. The CNN architecture had the ability to automatically extract important features from images, such as edges, textures, and other visual patterns, which makes it very suitable for the classification of objects or categories in images [16], [17], [18], [19]. This is done through convolution layers that enable the network to train and represent the relevant features of the input data as in Figure 4. This adaptive capability makes CNNs a highly effective tool in tasks such as the classification of breast tumors in medical images, where the identification of important patterns or features in images is a critical step in medical diagnosis and treatment.

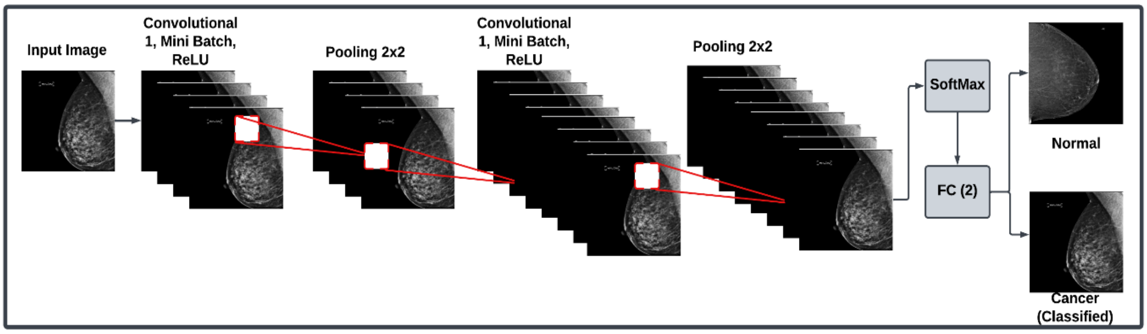


Figure 4. Proposed layer in CNN for breast tumor classification

Simple algorithm in CNN Architecture:

Load Image

Input image I with dimensions $W_{in} \times H_{in} \times D_{in}$, where W_{in} is Width, H_{in} is Height, and D_{in} is the number of dimensions with 3 channels for RGB color images.

$I = W_{in} \times H_{in} \times D_{in} = 256 \times 256 \times 3.$

Convolution Layer

Apply the convolution operation to the input image with K convolution filters F with dimensions $K_{Size} \times K_{size} \times D_{in}$ to produce C feature maps.

$$C_{i,j,k} = \sigma\left(\sum_{l=1}^{D_{in}}\sum_{m=1}^{K_{size}}\sum_{n=1}^{K_{size}} I_{i+m-1,j+n-1,l} \cdot F_{m,n,l,k} + b_k\right) \tag{1}$$

Where is the activation function (ReLU), i and j are the pixel indices on the feature map C, k is the filter index, l is the input channel index, m and n are the kernel dimension indices, I is the input image, F is the filter, b is biased.

ReLU Layer

Apply an activation function σ to each element in the feature map C to introduce non-linearity.

Pooling Layer

Apply pooling operations (for example, max pooling) on C feature maps to reduce dimensionality and complexity.

Fully Connected (FC) Layer

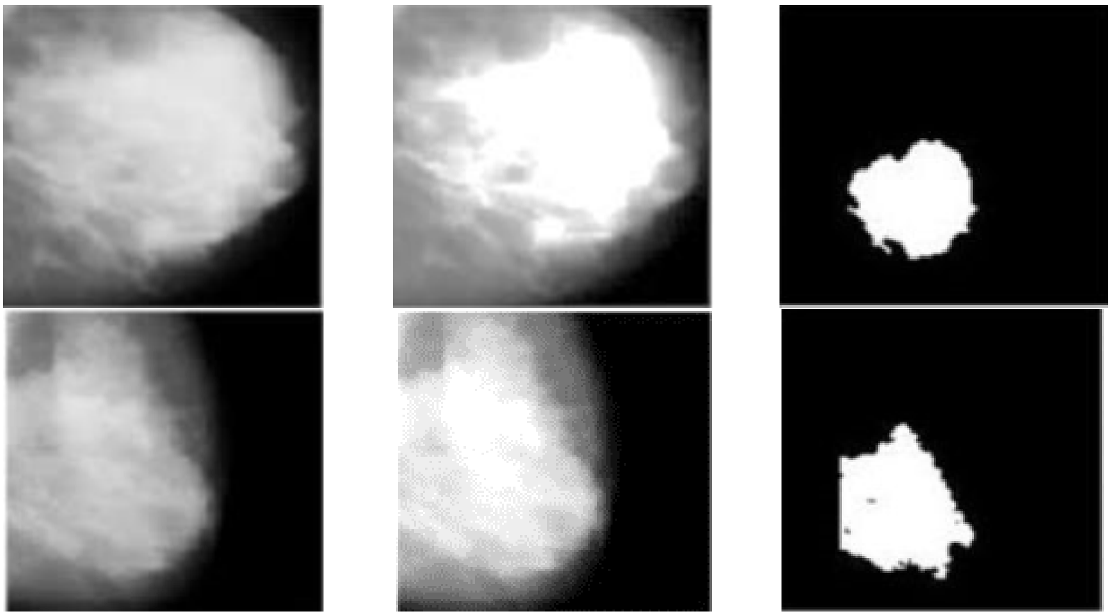
Apply a fully connected (FC) layer with W_{fc} weights and b_{fc} bias to generate a feature vector F_{fc}.

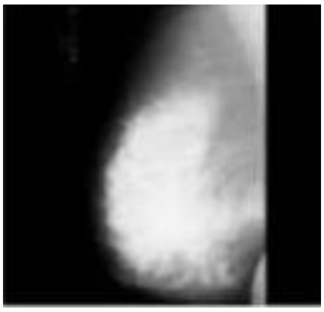
Output

Generate the final output using an appropriate output layer (e.g., softmax for classification) with W_{fc} weights and b_{fc} bias.

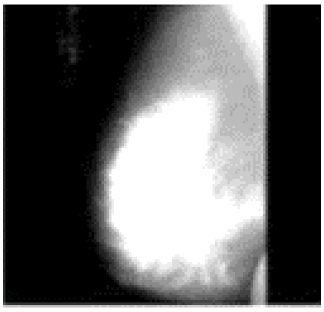
3. RESULTS AND DISCUSSIONS

The process begins with preprocessing and segmentation of breast cancer images. In the pre-processing stage, the raw images undergo normalization, noise removal, and handling of missing or incomplete data to improve data quality. Subsequently, segmentation techniques are applied to isolate relevant areas within breast images, enhancing the accuracy of tumor localization. The results of these preprocessing and segmentation steps are depicted in Figure 5, where (a) represents the original breast images, (b) illustrates the enhanced images after preprocessing, and (c) showcases the segmented images highlighting the tumor regions. This sequential approach ensures that the input data are adequately prepared and relevant features are accurately extracted, laying a solid foundation for subsequent classification tasks.

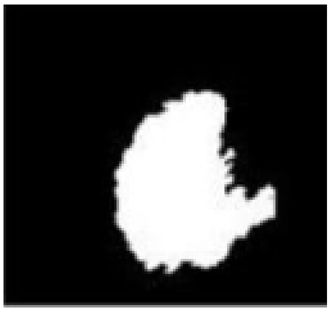




(a) Original Image



(b) Enhanced Image



(c) Segmented Image

Figure 5. Pre-processing phase

After pre-processing phase, on classification phase, we propose a method with Adam optimization. The experiment was carried out for 8 epochs with 32 and validation every 30 iterations. The initial learning rate used is 0.0001. After initializing the parameters according to the options mentioned, we succeeded in obtaining the results of the training graph as seen in Figure 6.

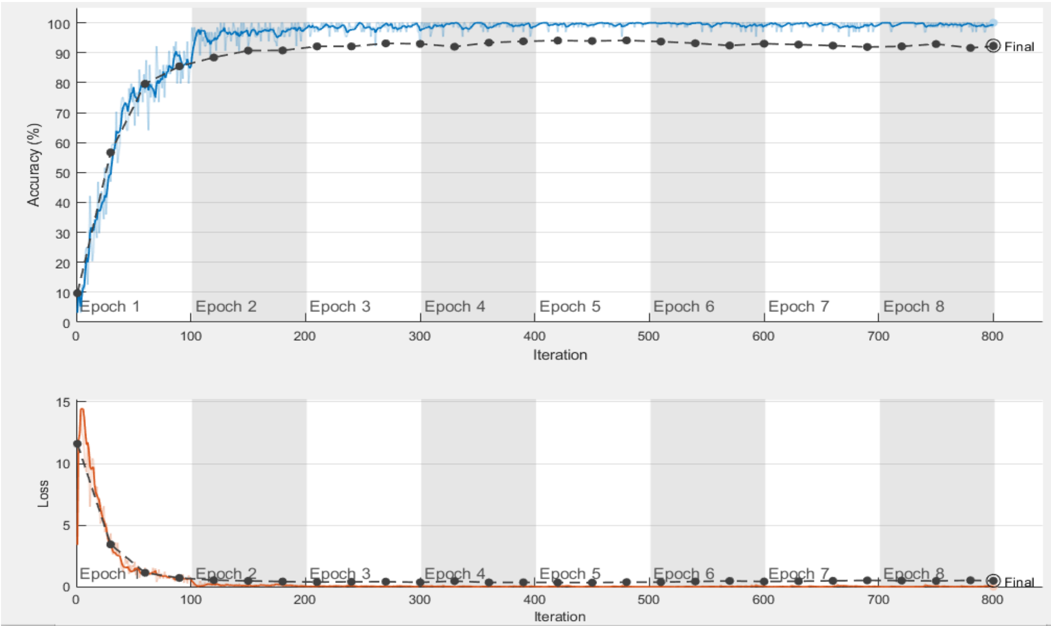


Figure 5. CNN based accuracy and loss graph

Figure 5 illustrates the accuracy and loss graphs for the CNN-based model in different epochs. In particular, from the third epoch to the final epoch, the graphs demonstrate significant convergence. This indicates that the model's accuracy improves steadily while the loss decreases, suggesting effective learning and optimization. The convergence observed from the third epoch onward highlights the stability and reliability of the model in classifying potential breast tumors, showcasing the efficacy of the CNN architecture and the optimization techniques employed, such as Optuna and the Adam optimizer. This consistent performance throughout the training process underscores the robustness and potential applicability of the model in real-world breast cancer detection and diagnosis scenarios.

After obtaining the final graph results at the end of the epoch, this study was measured using a confusion matrix. The confusion matrix evaluation provides a comprehensive assessment of the classification model's performance by breaking down the predicted and actual classification outcomes. The metrics derived from the confusion matrix, including accuracy, precision, recall, and F1 score, offer valuable insights into different aspects of the model's performance. High accuracy scores, reaching up to 99.72% in the first training session and averaging around 99.05% across all sessions, demonstrate the model's ability to correctly classify breast tumor data. Furthermore, metrics such as precision, recall, and F1 score, with values of approximately

98.3%, 100%, and 99.1% respectively, underscore the model's precision, sensitivity, and balanced performance in distinguishing between tumor and nontumor instances. Overall, the evaluation based on the confusion matrix highlights the robustness and effectiveness of the CNN-based classification model in accurately identifying breast tumors, validating its potential for practical application in healthcare settings. Based on confusion matrix equation can be seen below.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{2}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{4}$$

$$F1 - score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \tag{5}$$

Where, TP (True Positive) represents the number of instances correctly classified as positive (i.e. correctly identified breast tumor cases), TN (True Negative) denotes the number of instances correctly classified as negative (i.e., correctly identified nontumor cases), FP (False Positive) indicates the number of instances incorrectly classified as positive (i.e., non-tumor cases misclassified as tumor cases), and FN (False Negative) signifies the number of instances incorrectly classified as negative (i.e., tumor cases misclassified as non-tumor cases). Accuracy assesses the overall correctness of the model predictions by considering both true positive and true negative classifications. Precision quantifies the accuracy of positive predictions, focusing on the proportion of correctly predicted positive instances out of all instances predicted as positive. Recall, also known as sensitivity, measures the model's ability to correctly identify positive instances out of all actual positive instances. The F1 score, the harmonic mean of precision and recall, provides a balanced evaluation of the model's performance, considering both false positives and false negatives. Collectively, these metrics offer a comprehensive evaluation of the effectiveness in breast tumor classification.

Table 2. Evaluation result based on confusion matrix using proposed method

Evaluation Matrix	1st Training (80% Training Data)	2nd Training (75% Training Data)	Third Training (70% Training Data)	*Average*
Accuracy	99.72%	99.10%	98.32%	99.05%
Precision	99%	98%	98%	98.3%
Recall	100%	100%	100%	100%
F1-Score	99.5%	99%	99%	99.1%

This evaluation represents the confusion matrix, where the confusion matrix itself is a table used in evaluating the classification of machine learning models. This table is used to describe the performance of the model on a test data set, where the predicted results of the model are compared with the actual values (ground truth).

4. CONCLUSION

This study conducted three training sessions with varying percentages of training data (80%, 75% and 70%), demonstrating the effectiveness of a CNN-based model for the classification of breast tumors. The evaluation results reveal outstanding performance, with the highest accuracy of 99.72% achieved in the first training and an average accuracy of 99.05% across all sessions. Metrics such as precision, recall, and F1 score also yielded impressive results, with values of approximately 98.3%, 100%, and 99.1%, respectively. These results indicate that the model excels in accuracy (precision), sensitivity (recall), and balanced performance (F1-score), showcasing its significant potential for practical applications in the healthcare sector. The findings align with the expectations outlined in the Introduction, demonstrating that the integration of artificial intelligence technologies such as CNN, along with optimization techniques such as Optuna and Adam optimizer, can substantially enhance early breast cancer detection. The successful collaboration between medical professionals, scientists and AI experts has resulted in a robust model capable of contributing to improved diagnosis and treatment strategies.

Future research will focus on developing more sophisticated and precise predictive models leveraging larger and more representative data sets. Enhanced collaboration among scientists, medical practitioners, and information technology experts will be crucial to devising comprehensive strategies to address the challenges of breast cancer. This collaborative approach aims to improve early detection, improve patient outcomes, and ultimately increase quality of life and life expectancy for breast cancer patients. The promising results of this study pave the way for further advancements in breast cancer research and its application in clinical settings.

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