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Application of Convolutional Neural Networks for Classifying Invasive Ductal Carcinoma in Breast Cancer Histopathological Images

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Abstract

Invasive ductal carcinoma (IDC) is the most com- mon type of breast cancer, accounting for approximately 80% of cases. Accurate and early diagnosis of IDC is critical for effective treatment and improved patient survival rates. This study explores the use of convolutional neural networks (CNN) for the classification of IDC in histological breast tissue images, aiming to develop a computer-aided diagnostic (CAD) system that can support pathologists in identifying cancerous tissues. Using a public dataset of 5,547 labeled images, resized to 50x50 pixels to balance computational efficiency and the retention of diagnostically relevant features, we trained a CNN model optimized for binary classification (IDC vs. non-IDC). The preprocessing steps included image normalization and class balancing, with training and validation sets split in an 80:20 ratio. The CNN architecture utilized three convolutional layers with batch normalization and max-pooling, a dense layer with ReLU activation, and a final sigmoid-activated output layer. The model achieved an accuracy of 78%, with precision, recall, and F1-scores all at 0.78, and an area under the ROC curve (AUC) of 0.84, indicating effective discrimination between classes. These results suggest that CNN-based models hold promise for aiding in IDC diagnosis, although further research is needed to improve model performance. Future work will focus on exploring advanced architectures, data augmentation, and transfer learning to improve sensitivity and clinical applicability.

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1. INTRODUCTION

Invasive ductal carcinoma (IDC) is the most common type of breast cancer; about 8 out of 10 cases of breast cancer are invasive ductal carcinomas [1]. This is a type of cancer that, if not detected early, cancer cells originating in the breast ducts can invade surrounding tissue and eventually spread to other parts of the body, such as organs or bones, through the lymphatic system and bloodstream, forming metastases or secondary tumors [2]. For this reason, early and accurate diagnosis, which is essential for choosing the appropriate treatment plan and improving patient survival rates, has driven efforts in recent years to predict and detect all types of cancers through the use of artificial intelligence [3].

In the diagnosis of breast cancer, there are various screening methods, such as mammography, ultrasound, CT, MRI and other breast-specific studies; however, biopsy is the most widely used and effective approach to examining breast tissue, as it allows pathologists to access microscopic tissue structures through surgical incisions, resulting in digitized histopatho- logic images that allow differentiation between healthy, be- nign and malignant tissues [4]. A study by [5], which reviewed 270,000 cases over nine years, found that 1% of diagnoses resulted in false negatives or false positives, of which 67% of false negatives could have been prevented by additional screening or special pathologic methods and 44% of false positives could have been avoided with more liberal use of immunohistochemistry. These data show that interpretation of histopathological images represents a challenge due to the complexity of analyzing large volumes of tissue, as manual visual evaluation of specimens under the microscope, which depends on the specialist's knowledge and experience, faces limitations due to similarities in texture, color, and shape among tissue types, emphasizing the need for complementary tools to reduce poor or late diagnoses due to human bias [6].

In the face of these challenges, researchers have developed computer-aided diagnosis (CAD) systems. These systems in- crease diagnostic accuracy by reducing human error, helping pathologists make more accurate diagnoses [7]. Despite this, traditional methods used in these systems, such as gray- level co-occurrence matrix (GLCM) and scale-invariant trans- formations (SIFT), have significant limitations, as they rely on labeled data and require pathologists to manually select relevant features, which can lead to loss of information and difficulty in extracting meaningful features for classification; consequently, AI, and in particular deep learning (DL), ad- dresses these problems by automatically learning complex and hidden features from histopathological images, which improves classification accuracy and efficiency [8].

Among the deep learning-based techniques integrated with these CADs, convolutional neural networks (CNNs), a type of deep learning architecture, have shown high accuracy in detecting patterns indicative of IDC in medical images; For example, models such as AlexNet and ResNet, trained on large histological image databases such as PatchCamelyon and BreaKHis, can identify and classify malignant lesions at multiple levels of magnification with remarkable accuracy; moreover, recent studies have achieved accuracy rates of over 90%, distinguishing between invasive cancer, ductal carcinoma in situ (DCIS) and other benign conditions [9].

In view of the effectiveness of these techniques, in this research, a deep learning-based method is proposed to classify invasive ductal carcinoma into positive and negative categories from histopathological images.

2. LITERATURE REVIEW

Several studies have focused on the use of various clas- sification models, including CNN, for automatic detection and classification of invasive ductal carcinoma (IDC) in histopathologic images of breast cancer [4, 10–13]. For example, [14] proposed a detection system to di- agnose breast cancer by combining SVM, neural networks and Naive Bayes with feature selection methods achieving an accuracy of 98.82%. [11] presented methodologies for IDC prediction using CNN models, highlighting the use of various hidden layers within the CNN (3,5,7), the best results were obtained using the model with three hidden layers, achieving an average accuracy of 97% according to their performance metrics. In [4], a model for the classification of different grades within IDC was proposed, showing mostly hits within the model, giving about 93% within the *accuracy*, classifying the possible grades with great accuracy that can be presented in the histological images of this past study. In [10], a hybrid model called CNN-GRU was introduced for the detection of IDC-type breast cancer, standing out in the fact that it far outperforms other hybrid models, such as CNN-LSTM, and other existing ML/DL models, such as CNN, SVM or BiLSTM, giving as results of *accuracy*, *precision*, *sensitivity*, *specificity*, *F1- score* and AUC at 86.21%, 85.90%, 85.71%, 84.51%, 88% and 89%, providing a robust model against breast cancer diagnosis. To diagnose breast cancer, [12] used ResNet18 and metaheuristic algorithms such as Particle Swarm Optimization (PSO), Atom Search Optimization (ASO) and Equilibrium Optimizer (EO) to optimize extracted features to extract and optimize histopathological image features. With SVM and RBF functions, the approach achieves a *F-score* of 97.75% on the BreakHis dataset. [13] achieved the automation of IDC- type breast cancer diagnosis through the use of deep transfer learning supported Squeeze Net architecture using histological samples in the process, achieving an *accuracy* of 90.3%. [15] proposed a computer-aided diagnosis system to detect breast cancer using SVM, neural networks and Naive Bayes with the WDBC dataset, where it uses dimensionality reduction with LDA and then SVM, achieving an accuracy of 98.82% and an AUC of 99.94%. In [16], a tool was developed to classify and diagnose breast cancer, using HOG and GLCM to extract

key features from the images. Then, the SSO algorithm selects the best features and the S-ELFA method classifies benign and malignant tumors. [17] proposed a model to detect and classify breast cancer, achieving 99% accuracy in tests on CBIS- DDSM dataset and employing segmentation and classification techniques. Finally, [18] proposed a classifier assembled with *transfer learning* models (AlexNet, ResNet, MobileNetV2) for breast cancer detection. The results show accuracies of up to 99.17% in mini-DDSM and 96.92% in BUSI. Overall, these studies collectively demonstrate the growing interest and advances in the use of CNN models for IDC detection and classification in breast cancer histopathological images. Recent studies have also explored the use of advanced architectures in other domains, such as ViTAE-SL [19], a vision transformer-based autoencoder for spatial field reconstruction, and deep learning surrogate models for global wildfire prediction [20, 21]. These approaches highlight innovative modeling strategies that could be adapted for medical imaging tasks in future research.

3. METHODOLOGY

This project aimed to develop a CNN model to detect IDC in histological images of breast tissue. To achieve this purpose, we used the dataset presented in article [22], published on the Kaggle platform by means of two numpy files, where the X file represents the training data and the Y file represents the validation data. The total labeled images processed were 5,547 images, each of size 50x50 pixels, corresponding to tissue sections that have been labeled to indicate the presence or absence of IDC. The images were stored as NumPy arrays, optimizing loading and processing in a computational environment. Based on this, within FIGURE 1, the methodology that will guide the construction of the present work is proposed, focusing on data preprocessing, CNN model construction and analysis of the performance metrics of the model proposed in this research work.

3.1 Dataset

Each record in the data set consists of:

- Image: A color (RGB) breast tissue histology image of size 50x50 pixels. This resolution was selected based on previous studies [14, 22], that recommended this size to avoid the complexity of processing full-size images. In these studies, it was concluded that working with compact 50x50 pixel images facilitates model training without significant loss of relevant information for IDC detection. Although 50x50 resolution may omit certain micro-level details, this size was chosen to ensure model training feasibility without extensive computational resources, as supported by studies [14, 22]. Future work will consider higher-resolution images to evaluate the impact on fine-grained feature retention and diagnostic accuracy.
- Class: A binary label (1 for 'IDC' and 0 for 'non-IDC') indicating the presence of IDC in the image.

3.2 Data Preprocessing

1) Normalization: The images were transformed to values in the range [0, 1] by dividing each pixel value by 255.0. This allows the model to process the images more accurately and facilitates convergence during training.
2) Division of the data set: To train and evaluate the model, the data set was divided into a training set (80%) and a validation set (20%).
3) Class Balancing: Due to the difference in the number of images with and without IDC, class weights were computed to reduce the bias toward the majority class. This was done using scikit-learn's compute_class_weight function, which gives proportional weight to the classes during training, improving the model's ability to learn from both.

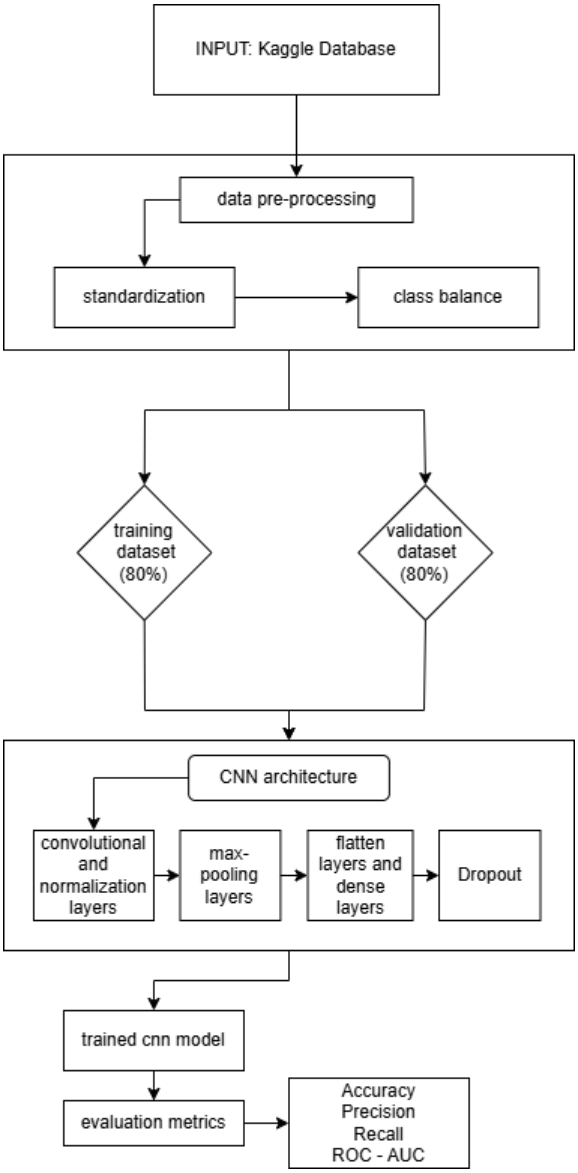

Figure 1: Flow diagram of the proposed methodology of this work. Adapted from [4].

4. DEVELOPMENT

4.1 Architecture

The network architecture (see TABLE 2) was designed to capture relevant image features, using convolutional layers that detect patterns in pixels to classify images into ’IDC’ and ’non-IDC’. The CNN configuration includes:

Table 1: Article Comparison.

Document	Models	Types of cancer	Accuracy	Datasets
[17]	YOLO, UNet, ResUNet, Associated-ResUNets, BreastNet-SVM, AlexNet	Breast cancer	99.16%	CBIS-DDSM
[16]	SVM, CNN, ANN, KNN,Naive Bayes, Desicion Tree, S-ELFA	Breast cancer	99.5%	BreakHis
[14]	SVM with RBF kernel, Artificial Neural Networks (ANN), Naïve Bayes Classifier (NBC)	Breast cancer	98.82%	WDBC by UCI Machine Learning Repository
[18]	AlexNet, ResNet, MobileNetV2	Breast cancer	99.17%	Kaggle
[12]	ResNet18, Support Vector Machine (SVM),K-Nearest Neighbor (KNN), Decision Tree (DT)	Breast cancer	97.73%	BreakHis
[15]	DeepBreastCancerNet, ResNet101, ResNet-50, ResNet-18, GoogLeNet, ShuffleNet, AlexNet, SqueezeNet, XceptionNet	Breast cancer	99.35%	Kaggle
[11]	3,7,8-hidden layer CNN	Breast cancer type IDC	85%	Sitio web de Janowczyk
[4]	3-hidden layer CNN	IDC type breast cancer (G-1, G-2, G-3)	92.81%	DatoBiox
[10]	Hybrid CNN-GRU, CNN-LSTM, CNN-BiLSTM	Breast cancer type IDC	86.21%	Kaggle
[13]	Transfer Learning with SqueezeNet architecture	Breast cancer type IDC	90.3%	Kaggle

1) Convolutional and Normalization Layers: The network has three convolutional layers of 3x3 size filters, interspersed with batch normalization layers (BatchNormalization), which allows stable propagation and reduces the risk of overfitting.

2) Max-Pooling Layers: Each convolutional layer is followed by a max-pooling layer of size 2x2, which reduces the dimensionality of the images and selects the most salient features.

3) Flatten Layer and Dense Layers: After the convolutional layers, a Flatten layer was used to convert the feature maps into a 1D vector to connect them to a dense layer of 64 neurons with ReLU activation, followed by an output layer with a single neuron and sigmoid function, which provides a binary probability that the image belongs to the ’IDC’ class.

Table 2: Convolutional neural network architecture for IDC Detection.

Layer (Type)	Filter/Units	Activation	Output Shape
Input Layer	-	-	(50, 50, 3)
Conv2D	32 (3x3)	ReLU	(48, 48, 32)
BatchNormalization	-	-	(48, 48, 32)
MaxPooling2D	2x2	-	(24, 24, 32)
Conv2D	64 (3x3)	ReLU	(22, 22, 64)
BatchNormalization	-	-	(22, 22, 64)
MaxPooling2D	2x2	-	(11, 11, 64)
Conv2D	64 (3x3)	ReLU	(9, 9, 64)
BatchNormalization	-	-	(9, 9, 64)
Flatten	-	-	(5184)
Dropout	0.5	-	(5184)
Dense	64	ReLU	(64)
BatchNormalization	-	-	(64)
Dense (Output)	1	Sigmoid	(1)

4) Dropout: A dropout layer with a rate of 0.5 was used to mitigate the risk of overfitting, increasing the model's ability to generalize to new data.

4.2 Compilation and Training

The model was compiled using the Adam optimizer with an initial learning rate of 0.0001 and the binary crossentropy loss function, which is suitable for binary classification problems. During training, the following metrics were monitored to evaluate the model performance:

- Area under the curve (AUC) (FIGURE 2).
- Confusion matrix. Fig (FIGURE 3).
- Accuracy (TABLE 1).
- Precision y Recall (TABLE 3).

Table 3: Model evaluation results for classification of IDC on histological images.

Class	Precision	Recall	F1-Score	Support
0	0.79	0.77	0.78	552
1	0.77	0.79	0.78	558
Accuracy		0.78		1110
Macro Average	0.78	0.78	0.78	1110
Weighted Average	0.78	0.78	0.78	1110

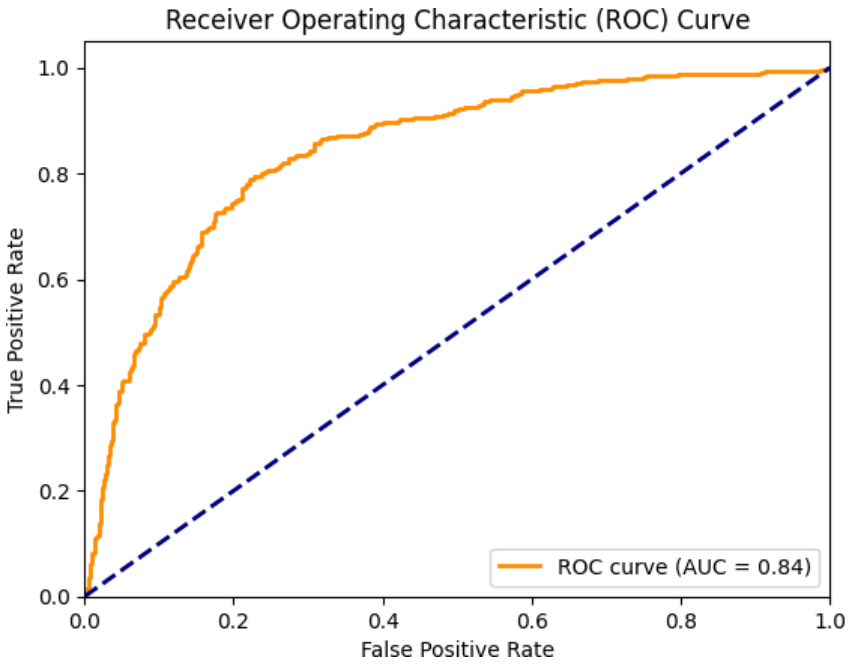

Figure 2: ROC - AUC

4.3 Validation

In addition to the validation tests of the CNN configuration with 20% of the data of the main dataset, additional tests were performed with another dataset [11], where the histological images were in png files that allowed unit tests with each image resulting in the confusion matrix, as shown in FIGURE 3, and FIGURE 4.

However, future studies should include multi-center datasets to evaluate the model's adaptability to variations in staining techniques, scanner types, and demographic diversity.

5. RESULTS

This study applied a convolutional neural network (CNN) for binary classification of histological images of breast tissue into cancer and non-cancer, focusing on the identification of invasive ductal carcinoma (IDC). The database used consists of 5547 records in NumPy format, with images of size 50x50 pixels that were selected at this size based on previous studies suggesting that relevant histological features are preserved at this resolution. This size is ideal for handling the data computationally without significant loss of information for the detection targets.

The trained model achieved an accuracy of 78%, evaluated in an independent validation set. Key metrics obtained in the classification include a precision of 0.78, a recall of 0.78, and an F1-score of 0.78 for both classes (IDC and non-IDC). TABLE 3 details the results by class, which allows us to visualize the model's ability to differentiate between the two types of images.

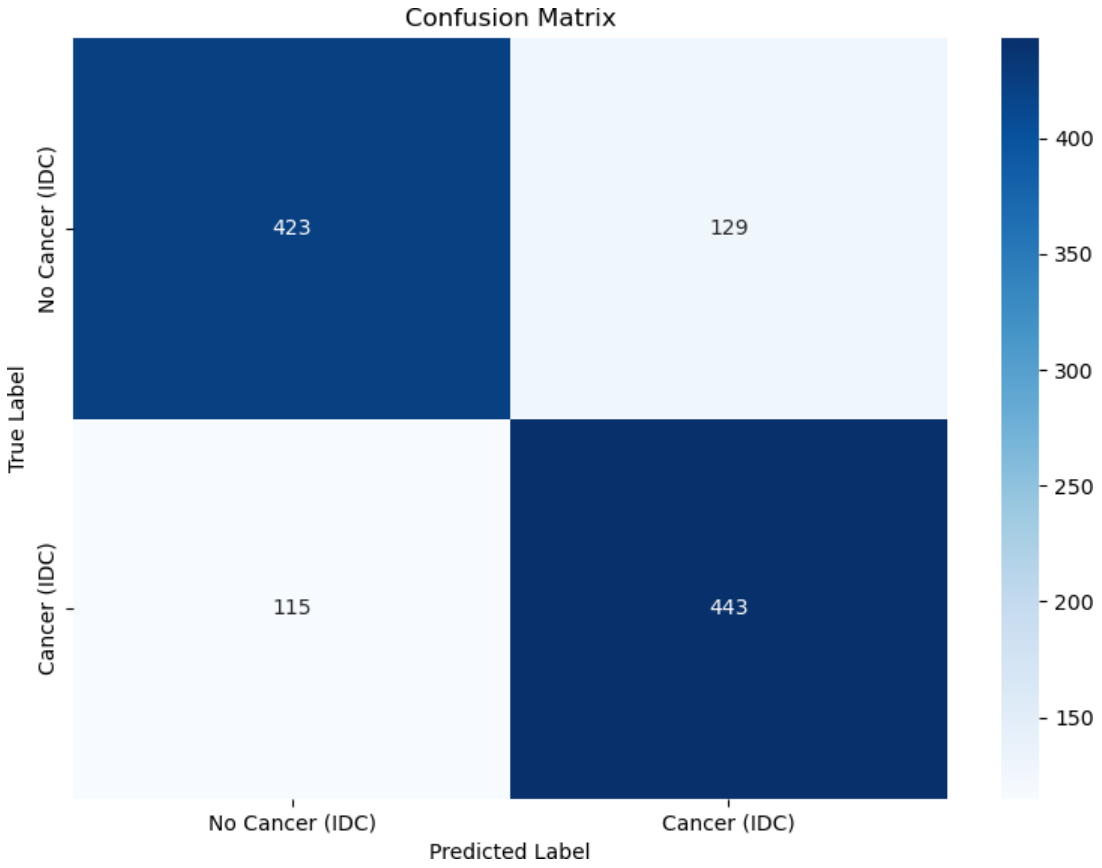

Figure 3: Confusion matrix

In addition to the accuracy metrics, the model obtained an area under the ROC curve (ROC-AUC) of 0.84. This result suggests that CNN performs well in distinguishing between positive and negative classes, which is crucial for diagnosis and helps mitigate the risk of false positives and false negatives in a clinical setting.

Although the model shows promising performance, there are areas for improvement. No tests were performed with alternative architectures or additional adjustments in image preprocessing, which could potentially improve the accuracy of the model. In addition, the size of the input images was kept at 50x50 pixels due to computational limitations and based on previous studies. Future research could explore data augmentation techniques, more complex architectures and more sophisticated preprocessing to improve model sensitivity in the context of clinical applications.

6. CONCLUSIONS

This study demonstrates the effectiveness of using convo- lutional neural networks (CNN) in histological image clas- sification for the detection of invasive ductal carcinoma in breast cancer. The model achieved an accuracy of 78% and an AUC of 84%, indicating good performance in distinguishing between cancer and non-cancer images. These results suggest that CNNs can be a useful

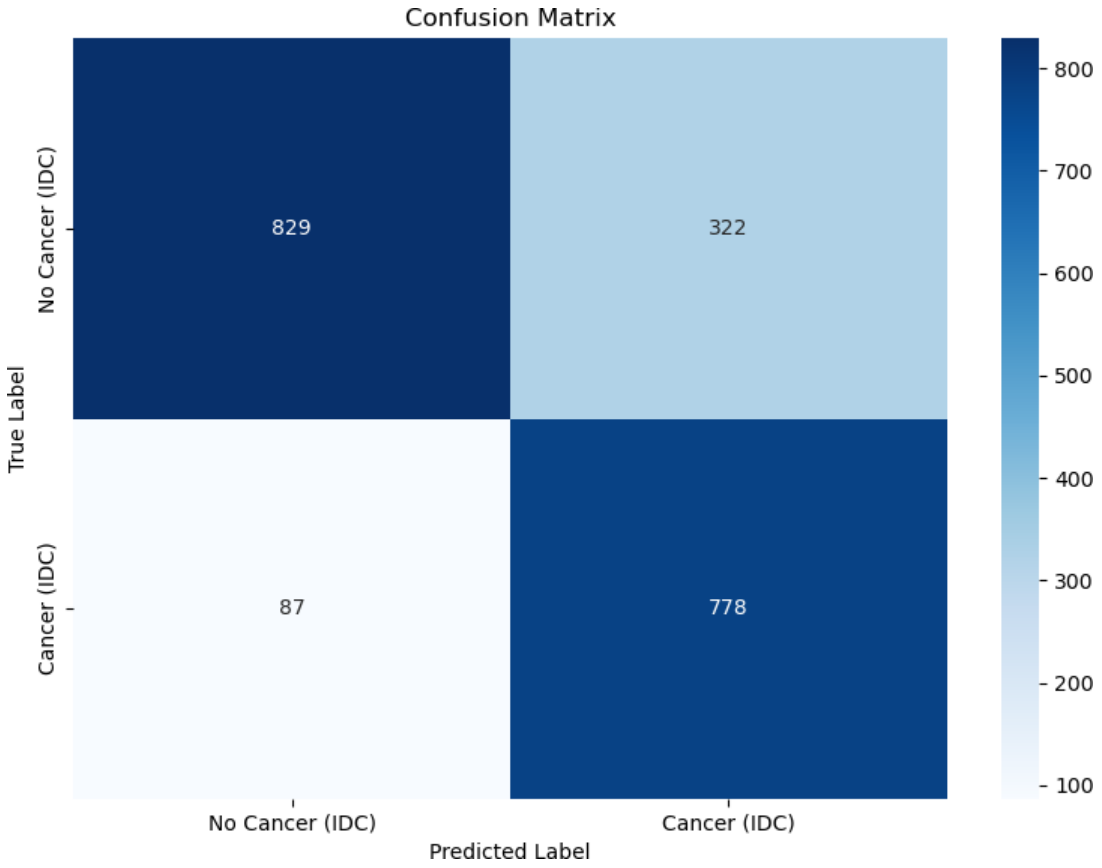

Figure 4: Confusion matrix - Validation

tool in computer-aided diagnosis, helping pathologists make more accurate diagnoses and reducing the workload in histological image evaluation. Although the CNN architecture used is standard, it provides a reliable performance benchmark for IDC classification in constrained computational environments. Future work will investigate more sophisticated models such as residual networks, vision transformers, or attention-guided CNNs to improve diagnostic capability.

7. RECOMMENDATIONS

Future research may focus on the evaluation of more advanced architectures and the use of data augmentation techniques to improve model sensitivity in clinical scenarios. In addition, the implementation of transfer learning algorithms could help increase the accuracy of IDC detection, allowing progress towards increasingly robust and accurate diagnostic tools.

8. LIMITATIONS

It is important to consider that this research has limitations, including the use of a single type of architecture, a deep learning algorithm (CNN) and the resolution of the images (50x50). Another limitation is the limited diversity of the datasets used. Broader validation across multiple institutions and acquisition settings is necessary to ensure the model's robustness in real-world clinical environments.

9. DECLARATION OF CONFLICT OF INTEREST

The authors have no conflicts of interest.

References

[1] https://www.cancer.org/es/cancer/tipos/cancer-de-seno/acerca/tipos-de-cancer-de-seno/cancer-invasivo-del-seno.html

[2] Kanadath A, Jothi JA, Urolagin S. Enhancing IDC Histopathology Image Classification: A Comparative Study of Fine-Tuned and Pre-trained Models. In International Conference on Soft Computing and its Engineering Applications. Cham: Springer Nature Switzerland. 2023:164-176.

[3] Bolhasani H, Amjadi E, Tabatabaeian M, Jassbi SJ. A Histopathological Image Dataset for Grading Breast Invasive Ductal Carcinomas. Informatics in Medicine Unlocked (IMU). 2020;19:100341.

[4] Talpur S, Rashid M, Khan SJ, Syed SA. Automatic Detection System to Identify Invasive Ductal Carcinoma by Predicting Bloom Richardson Grading from Histopathological Images. JISR on Comput (JISR-C). 2022;20.

[5] Renshaw AA, Gould EW. Reducing False-Negative and False-Positive Diagnoses in Anatomic Pathology Consultation Material. Arch Pathol Lab Med. 2013;137:1770-1773.

[6] AKaur A, Kaushal C, Sandhu JK, Damaševičius R, Thakur N. Histopathological Image Diagnosis for Breast Cancer Diagnosis Based on Deep Mutual Learning. Diagn. 2023;14:95.

[7] Kumaraswamy E, Kumar S, Sharma M. An Invasive Ductal Carcinomas Breast Cancer Grade Classification Using an Ensemble of Convolutional Neural Networks. Diagn. 2023;13:1977.

[8] Abdolahi M, Salehi M, Shokatian I, Reiazi R. Artificial Intelligence in Automatic Classification of Invasive Ductal Carcinoma Breast Cancer in Digital Pathology Images. Med J Islam Repub Iran. 2020;34:140.

[9] Islam T, Hoque ME, Ullah M, Islam T, Nishu NA, et al. CNN□Based Deep Learning Approach for Classification of Invasive Ductal and Metastasis Types of Breast Carcinoma. Cancer Med. 2024;13:e70069.

[10] Wang X, Ahmad I, Javeed D, Zaidi SA, Alotaibi FM, et al. Intelligent Hybrid Deep Learning Model for Breast Cancer Detection. Electron. 2022;11:2767.

[11] de Assis ÉG, do Patrocínio ZK, Nobre CN. The Use of Convolutional Neural Networks in the Prediction of Invasive Ductal Carcinoma in Histological Images of Breast Cancer. Stud Health Technol Inform. In MedInfo. 2021;290:587-591.

[12] Atban F, Ekinci E, Garip Z. Traditional Machine Learning Algorithms for Breast Cancer Image Classification with Optimized Deep Features. Biomed Signal Process Control. 2023;81:104534.

[13] Chaudhury S, Sau K, Khan MA, Shabaz M. Deep Transfer Learning for IDC Breast Cancer Detection using Fast AI Technique and Sqeezenet Architecture. Math Biosci Eng. 2023;20:10404-10427.

[14] Omondiagbe DA, Veeramani S, Sidhu AS. Machine Learning Classification Techniques for Breast Cancer Diagnosis. IOP Conf. Ser. Mater. Sci. Eng. IOP Publishing. 2019;495:012033.

[15] Raza A, Ullah N, Khan JA, Assam M, Guzzo A, et al. DeepBreastCancerNet: A Novel Deep Learning Model for Breast Cancer Detection Using Ultrasound Images. Appl Sci. 2023;13:2082.

[16] Khan AI, Abushark YB, Alsolami F, Almalawi A, Alam MM, et al. Prediction of Breast Cancer Based on Computer Vision and Artificial Intelligence Techniques. Measurement. 2023;218:113230.

[17] Ahmad J, Akram S, Jaffar A, Ali Z, Bhatti SM, et al. Deep Learning Empowered Breast Cancer Diagnosis: Advancements in Detection and Classification. PLoS one. 2024;19:e0304757.

[18] Sahu A, Das PK, Meher S. An Efficient Deep Learning Scheme to Detect Breast Cancer Using Mammogram and Ultrasound Breast Images. Biomed Signal Process Control. 2024;87:105377.

[19] Chen C, Li L, Aly MM. ViTA: A Highly Efficient Dataflow and Architecture for Vision Transformers. In 2024 Design, Automation & Test in Europe Conference & Exhibition (DATE). IEEE. 2024;65:1-6.

[20] Fan H, Cheng S, de Nazelle AJ, Arcucci R. ViTAE-SL: A Vision Transformer-Based Autoencoder and Spatial Interpolation Learner for Field Reconstruction. Comput Phys Commun. 2025;308:109464.

[21] Fan H, Cheng S, de Nazelle AJ, Arcucci R. An Efficient ViT-Based Spatial Interpolation Learner for Field Reconstruction. In International Conference on Computational Science (ICCS). Cham: Springer Nature Switzerland. 2023:430-437.

[22] Janowczyk A, Madabhushi A. Deep Learning for Digital Pathology Image Analysis: A Comprehensive Tutorial with Selected Use Cases. J Pathol Inform. 2016;7:29.