Chapter

BCNet: A Novel Deep Learning Model for Enhanced Breast Cancer Classification Using Histopathological Images

Mikiyas Amare Getu, Chao Lu, Yumeng Liu, Anam Mehmood, Zoya Iqbal and Xianbin Zhang

Abstract

Breast cancer is the most commonly diagnosed cancer among women and a leading cause of cancer-related deaths globally, necessitating accurate and timely diagnosis for effective treatment. Histopathological examination of breast tissue samples is the gold standard for diagnosing breast cancer, but this process is subjective, time-consuming, and reliant on the level of the pathologist's expertise. This study introduces a new deep learning model, Breast Cancer Network (BCNet), specifically designed to detect and classify breast cancer. BCNet, a 22-layer convolutional neural network (CNN), aims to enhance diagnostic accuracy by capturing high-level discriminative features tailored to breast tissue images. The BCNet model was evaluated against established CNN models, demonstrating superior performance, achieving an accuracy of up to 99.8% for binary classification and 99.6% for multi-class classification at different magnifications. These results highlight BCNet's robustness and potential to reduce diagnostic errors and assist pathologists. Future research should explore the generalizability of BCNet across larger datasets and its integration into clinical workflows to provide real-time, AI-assisted diagnostic support.

Keywords: breast cancer, BCNet, convolutional neural network, deep learning, histopathological images

1. Introduction

Breast cancer ranked as the second leading cause of global cancer incidence in 2022, with an estimated 2.3 million new cases, accounting for 11.6% of all cancer cases. Among women, breast cancer is the most commonly diagnosed cancer and remains the leading cause of cancer-related deaths globally [1]. This emphasizes a critical need for accurate and timely diagnosis to ensure effective treatment and improved patient outcomes.

Histopathological analysis of breast tissue samples remains the gold standard for diagnosing breast cancer. This method involves the microscopic examination of tissue lesions through tissue sections stained with hematoxylin and eosin to distinguish between benign and malignant tumors [2]. However, the accuracy of this model heavily depends on the expertise of pathologists, making it subject to variability, potential diagnostic errors, and time-consuming procedures [3]. Additionally, there is a global shortage of experienced histopathologists, particularly in underdeveloped countries and small hospitals [4]. The diagnosis by histopathologists is inherently subjective, lacking an objective evaluation basis. Therefore, there is an urgent need for an efficient and objective breast cancer diagnostic method to alleviate the workload of histopathologists [5].

Advancements in artificial intelligence, particularly deep learning, offer a promising solution by providing accurate and consistent diagnostic tools, potentially transforming breast cancer diagnosis [6]. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated exceptional performance in various image classification tasks, including medical image analysis [7]. Using CNNs for breast cancer detection and classification can potentially reduce diagnostic errors, expedite the diagnostic process, and assist pathologists by providing reliable second opinions [8].

Several studies have compared different CNN models for classifying benign and malignant breast cancer images. For example, one study compared models such as VGG16, VGG19, InceptionV3, and ResNet50 [9]. Another study combined a CNN model with Long Short-Term Memory (LSTM) networks to classify benign and malignant tumors [10]. Additional research has adapted the InceptionV3 and Inception_ResNetV2 architectures to address both binary and multi-class breast cancer classification issues [11]. Furthermore, a study on breast cancer detection and classification using pre-trained models, including Xception, InceptionV3, ResNet50, VGG16, and MobileNet, along with a proposed model called BCCNN, found that BCCNN achieved the highest accuracy [12]. However, these studies have primarily relied on pre-trained models through transfer learning. While transfer learning leverages the power of existing state-of-the-art CNNs, it often faces limitations such as the dependency on the source domain's features, which may not capture the intricate patterns of histopathological images [13]. These models may also suffer from decreased performance due to domain mismatch and the risk of overfitting when fine-tuned on relatively small histopathological datasets [14].

In this study, we aim to develop a new deep learning CNN model called BCNet (Breast Cancer Network) specifically designed to detect and classify breast cancer using histopathological images from the Breast Cancer Histopathological Image Classification (BreakHis) dataset [15]. BCNet addresses the limitations of pre-trained models by incorporating architecture and training strategies tailored to the unique characteristics of breast tissue images, potentially enhancing accuracy. Although BCNet shares foundational components with pre-existing CNN models, it introduces a novelty that optimizes it specifically for breast cancer histopathology. BCNet includes custom feature extraction layers designed to capture the unique features and morphology of breast tissue images, which differentiates it from models like ResNet [16] and VGG [17] which are designed for general-purpose image classification. Additionally, BCNet integrates domain-specific modifications such as customized layers, batch normalization, and dropout techniques tailored to unique requirements for breast tissue images.

The novelty of BCNet's model lies in focusing on domain-specific features rather than a generalized CNN architecture. Unlike general CNN models like DenseNet [18] or ResNet [16], BCNet includes domain-specific optimizations such as tailored magnification handling and advanced data augmentation techniques to enhance its ability to capture fine-grained histological features, improving its diagnostic accuracy. Furthermore, BCNet is specially designed to address the challenges of breast cancer histopathology, such as the variety of image magnifications, including 40X, 100X, 200X, and 400X, and class imbalances between benign and malignant samples [15].

Our proposed BCNet model aimed to enhance the diagnostic accuracy of histopathological image classification by learning complex patterns within the images. We compared the performance of BCNet with existing state-of-the-art CNN models, including VGGNet [17], AlexNet [19], DenseNet [18], and ResNet [16], to demonstrate its effectiveness and superiority in breast cancer diagnosis. Through the use of CNN, we aim to address the challenges in breast cancer histopathology, ultimately contributing to improved diagnostic precision and patient care.

2. Methods

Figure 1 illustrates the process of inputting data for both binary and multi-class classification, combining the features from these classifications, pre-processing, BCNet model development, and the comparison of its performance with existing models.

2.1 Dataset

The Breast Cancer Histopathological Image Classification (BreakHis) is a large-scale dataset composed of 7909 microscopic images of breast tumor tissue collected from 82 patients. BreaKHis is divided into benign and malignant breast tumors with

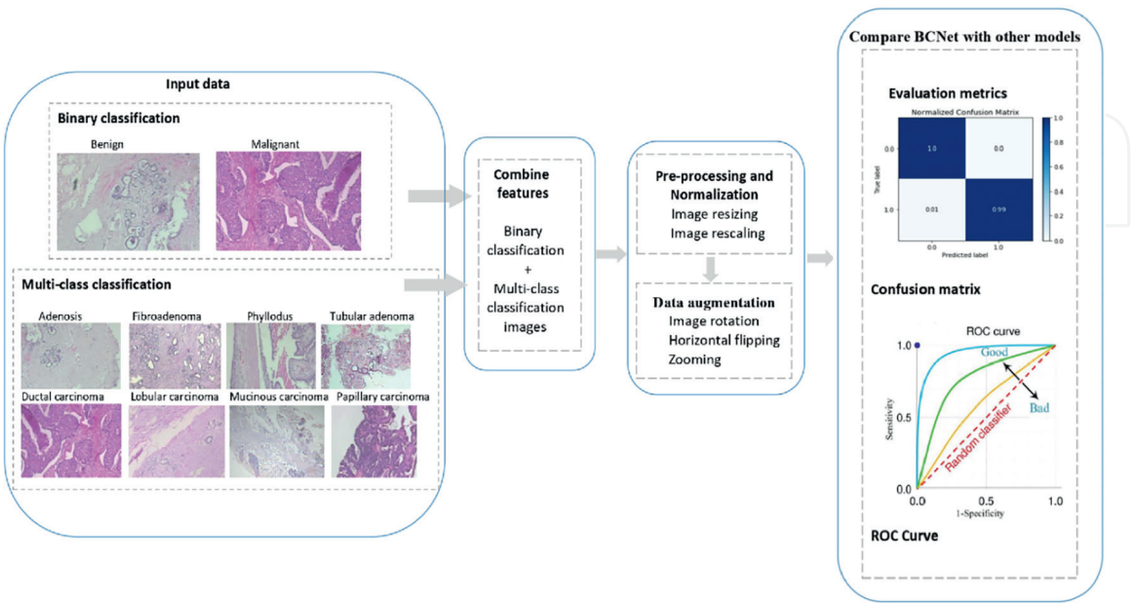

Figure 1.
Study flow.

Tumor subtypes	Magnification factors				
	Number of patients	40x	100x	200x	400x
Benign					
Adenosis	4	114	113	111	106
Fibroadenoma	10	253	260	264	237
Tubular adenoma	3	109	121	108	115
Phyllodes adenoma	7	149	150	140	130
Malignant					
Ductal carcinoma	38	864	903	896	788
Lobular carcinoma	5	156	170	163	137
Mucinous carcinoma	9	205	222	196	169
Papillary carcinoma	6	145	142	135	138
Total	82	1995	2081	2013	1820

Table 1.
Benign and malignant tumor classification with respect to magnification factors.

four magnification factors: 40X, 100X, 200X, and 400X. Both benign and malignant breast tumors are classified into distinct subtypes. The benign breast tumor is classified into adenosis, fibroadenoma, phyllodes tumor, and tubular adenoma. Whereas the malignant breast tumor is classified into ductal carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma. The classification and size of the BreakHis is described in **Table 1**. The dataset used in this study was published by Spanhol et al. [20] and it can be accessed through the following link https://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis/.

2.1.1 Splitting dataset

To ensure the generalizability of the experimental outcomes in the classification assignment, the datasets with four magnification levels were randomly divided into training, validation, and testing sets at a ratio of 0.7:0.15:0.15.

2.2 Image pre-processing

Image pre-processing plays a crucial role in enhancing the quality and utility of breast cancer histology images for subsequent analysis and classification tasks. The pre-processing steps typically involve several key procedures aimed at standardizing and optimizing the images for accurate interpretation by machine learning models. It significantly affects the detection and classification results of breast cancer. Firstly, the images are resized to 256*256 pixels to ensure uniformity in dimensions, facilitating efficient processing and comparison across samples. This step is particularly important because the images were captured at different magnification levels.

Secondly, normalization techniques such as rescaling 1./255 were applied to adjust the intensity values across the images. This process enhances the contrast and visibility of important features within the tissue samples, aiding in the detection of relevant patterns by classification algorithms. Additionally, color normalization was done based on RGB channels to standardize the color distribution across images, reducing

variability due to differences in staining protocols or imaging conditions. This step ensures consistency in the appearance of tissue features, facilitating more robust and reliable classification outcomes.

2.3 Data augmentation

To address issues such as overfitting and imbalanced class distributions, we performed data augmentation techniques on the dataset. This was achieved using the ImageDataGenerator function within Keras, allowing us to apply image rotations of up to ±20 degrees, horizontal flipping, as well as shifts in width and height (set at 0.2), shearing (0.2), and zooming (0.2). The classes within the breast tumor dataset exhibited an imbalance, particularly with a significant number of ductal carcinoma instances in malignant tumors and fibroadenoma instances in benign tumors, resulting in a Gaussian distribution pattern [21]. We implemented an oversampling method using the aforementioned data augmentation strategies to balance the number of images across each class of breast cancer histopathology.

2.4 Breast cancer network (BCNet) model development

Breast Cancer Network (BCNet) is a proposed model consisting of 22 layers with an input shape of (256 x 256 x 3). BCNet is a newly developed CNN model for detecting and classifying breast cancer. The output of the model is classified into 8 classes, which include adenosis, fibroadenoma, phyllodes tumor, tubular adenoma, ductal carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma. The proposed model contains input, convolutional, pooling, and dense layers, and a fully connected layer including a SoftMax activation function.

2.4.1 BCNet model architecture and training parameters

Table 2 summarizes the architecture and parameters of our newly developed deep learning model for classifying benign and malignant subtypes of breast cancer histopathology images. The input layer of the model processes images with dimensions of 256 x 256 x 3, accommodating the RGB channels. The model employs a Conv2D layer with 32 filters of size 3x3 for feature extraction. This is helpful for capturing fine-grained details in histopathological images for identifying different cancer subtypes. A filter size of 3*3 facilitates the model learning process. Following the convolutional layer, a MaxPooling2D layer with a 2x2 pool size is used to reduce the spatial dimensions of the feature maps [7, 22]. MaxPooling is important in the downsampling of the feature maps, reducing the number of parameters and computation to retain important tumor features. Batch normalization is applied to stabilize and accelerate the training process, particularly in complex tasks such as histopathological analysis. The Rectified Linear Unit (ReLU) activation function [23] is used to introduce non-linearity, allowing the model to learn complex representations. The model is trained using the categorical cross-entropy loss function, suitable for multi-class classification tasks.

The architecture includes a batch size of 32 and a SoftMax activation function in the output layer to classify the images into one of the eight predefined classes. The SoftMax function converts raw model predictions into probabilities, which improves model interpretability. The Adam optimizer, with a learning rate of 0.001, is employed to adjust the weights during training. A dropout rate of 0.5 is incorporated

Model parameters	Values
Input layer	256 x 256 x 3
Channels	3(RGB)
Convolutional	Conv2D (32 (3, 3))
Pooling	Maxpooling2D (2, 2)
Batch Normalization	Yes
Activation	ReLU
Loss	Categorical_crossentropy
Batch size	32
Activation function	SoftMax
Class	8
Optimizer	Adam
Learning rate	0.001
Drop out	0.5
Metrics	Accuracy
Number of epochs	20

Table 2.
Parameters and hyperparameters used for BCNet model development.

to prevent overfitting by randomly dropping neurons during training. This dropout technique helps to ensure that the model is not dependent on a single neuron, which might affect the generalizability of the model to new data, which is particularly useful for clinical applications where the consequence of overfitting is significant. The model's performance is evaluated using accuracy as the primary metric, and training is conducted over 20 epochs to ensure sufficient learning while avoiding the risk of overfitting. This configuration aims to achieve a robust and accurate classification of breast cancer histopathology images.

This model has a complex architecture used to learn the intricate or complex patterns of the histology images, and it has approximately 6.7×10^7 parameters.

BCNet was a deep learning CNN model used to perform binary and multi-class classification of histopathological images of breast cancer.

2.5 Model performance evaluation metrics

Evaluation metrics play a crucial role in assessing the performance of deep learning models, particularly in the context of medical image analysis such as breast cancer detection [24]. The following evaluation metrics include accuracy [24, 25]; recall (sensitivity), specificity [26, 27]; precision [28–30]; ROC, and area under the curve (AUC) [31].

2.5.1 Confusion matrix

A confusion matrix is a valuable tool used to evaluate the performance of a classification model by comparing the predicted and actual class labels of a dataset.

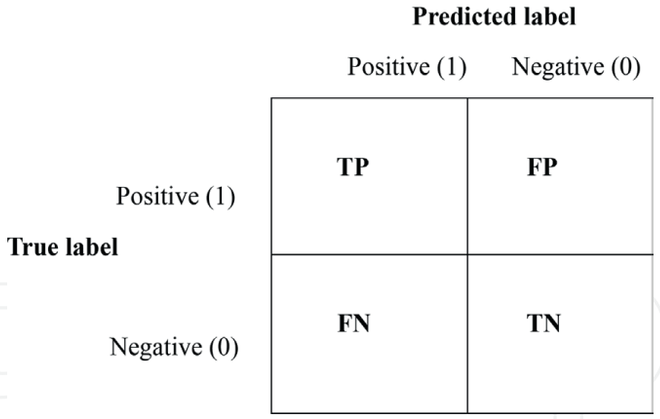

Figure 2.
Confusion matrix for classification report.

It provides a clear summary of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) predicted by the model. **Figure 2** illustrates a sample confusion matrix, presenting predictions based on their accuracy. This matrix serves as a basis for calculating metrics like ROC curve, recall, specificity, accuracy, and others, offering insights into the model's classification capabilities [31].

2.5.2 Accuracy

Accuracy measures how much the model correctly predicts the outcome.

$$Accuracy = \frac{TP + FP}{TP + FN + FP + TN}$$

2.5.3 Precision

Precision is an evaluation metric that quantifies the ratio of correctly predicted positive cases to all predicted positive cases, emphasizing the model's ability to avoid false positives.

$$Precision = \frac{TP}{TP + FP}$$

2.5.4 Sensitivity

Sensitivity, also referred to as true positive rate (TPR), is a performance metric in classification that gauges the model's accuracy in identifying positive cases correctly. It is calculated as the ratio of true positives (P1) to the total of actual positive cases (P1 + N1), represented as a percentage or a decimal ranging from 0 to 1. Sensitivity is mathematically expressed as:

$$Sensitivity = \frac{TP}{TP + TN}$$

2.5.5 Specificity

Specificity complements recall by measuring the model's ability to correctly identify negative cases out of all actual negative cases.

$$Specificity = \frac{TN}{TN + FP}$$

2.5.6 ROC curve and AUC

The ROC curve serves as a visual representation of a binary classification (benign and malignant) model's performance across various classification thresholds, comparing the true positive rate (TPR) to the false positive rate (FPR). A superior model exhibits a higher TPR and a lower FPR. The curve showcases the TPR-FPR balance, with the area under the curve (AUC) reflecting overall performance; a perfect model has an AUC of 1.0, while a random model scores 0.5. Moving toward the top-left corner in the ROC space signifies an improved classifier accuracy, with a higher TPR and lower FPR, thus enhancing positive case identification while minimizing false positives.

3. Results

We employed our newly developed BCNet model for both binary and multi-class classification of histopathological breast cancer images, comparing its performance with existing state-of-the-art CNN models. After pre-processing the data, we applied data augmentation techniques, including rotation, horizontal flipping, shearing, zooming, scaling, and color normalization. Additionally, we resized the images to ensure uniform dimensions.

During the training process, the neural network model was iteratively refined until the loss converged to $1e^{-02}$, optimizing the weights to improve accuracy.

Current studies on histopathological images of breast cancer predominantly focus on binary classification. However, multi-class classification is crucial for accurate treatment and prognosis. Therefore, we conducted a multi-class classification study using BCNet. The experimental results of our model improved the diagnostic accuracy of using histopathological breast cancer images.

3.1 Model prediction

Evaluation metrics are essential for assessing the performance of deep learning models, especially in medical image analysis, such as breast cancer detection [24]. To evaluate the classification of benign and malignant cancer images, we utilized metrics including accuracy, sensitivity, specificity, ROC, and AUC curves for both binary and multi-class classifiers. These metrics were derived from the confusion matrix, considering true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

Our proposed BCNet model's binary classifier achieved remarkable accuracy for images at different magnifications: 99.6% for 40X, 99.8% for 100X, 99.7% for 200X, and 99.1% for 400X (see **Table 3**). These results demonstrate the model's high efficacy in distinguishing between benign and malignant breast cancer images.

Type of classification	Magnification factor	Accuracy (%)	Sensitivity (%)	Specificity (%)
Binary classifier	40X	99.6	98.1	99.6
	100X	99.8	97.3	99.9
	200X	99.7	98.9	99.6
	400X	99.1	97.3	98.2
Multi-class classifier	40X	99.1	98.1	97.6
	100X	98.3	96.5	98.9
	200X	99.6	98.7	98.6
	400X	98.9	96.3	98.2

Table 3.
BCNet model performance metrics for binary and multi-class classification of breast cancer.

The proposed BCNet model multi-class classifier for 40×, 100×, 200×, and 400× images showed an accuracy of 99.1, 98.3, 99.6, and 98.9%, respectively, as shown in **Table 3**.

The BCNet model outperformed the existing CNN models for both the binary and the multi-class classifiers, as reported in **Table 4**.

3.1.1 Confusion matrix for a binary classifier

The confusion matrix of the binary classifier for the BCNet model, as depicted in **Figure 3**, demonstrates that our proposed model correctly classified 626 out of 628 samples, 897 out of 903 samples, 777 out of 780 samples, and 595 out of 600 samples.

Study	Classifier	Dataset	Accuracy (%)			
			40x	100x	200x	400x
Binary classification [32]	ResNet152	Breakhis	98.6	97.9	98.3	97.6
[33]	NDCNN	Breakhis	94.4	95.9	97.2	96.0
[34]	GoogleNet	Breakhis	94.8	94.4	94.7	93.5
[35]	NDCNN	Breakhis	95.8	96.9	96.7	94.9
[36]	VGGnet	Breakhis	91.2	91.4	88.5	84.5
[37]	AlexNet	Breakhis	90.6	90.5	91.3	91.3
[38]	DenseNet	Breakhis	94.7	95.9	96.7	89.1
Proposed model	BCNet	Breakhis	99.6	99.8	99.7	99.1
Multi-class classification [32]	ResNet152	Breakhis	95.6	94.8	95.6	94.6
[35]	NDCNN	Breakhis	92.8	93.9	93.7	92.9
[39]	NDCNN	Breakhis	88.2	84.6	83.1	83.9
[10]	CNN-RNN hybrid	Breakhis	96.5	92.6	88.9	92.5
Proposed model	BCNet	Breakhis	99.1	98.3	99.6	98.9

Table 4.
Binary and multi-class classification models comparison with existing state-of-the-art models.

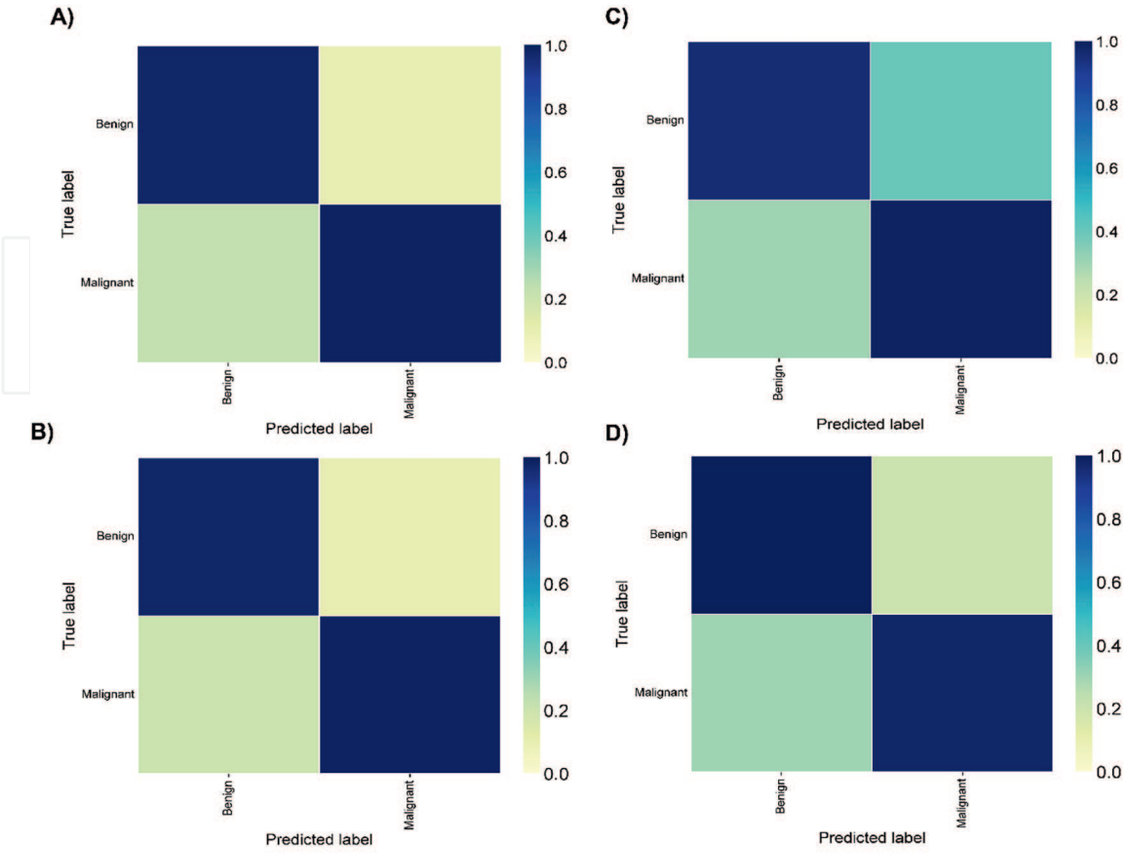

Figure 3.
BCNet model binary classifier confusion matrix at different magnification levels: 40× (A), 100× (B), 200× (C), and 400× (D).

3.1.2 ROC-AUC curve analysis for the BCNet model in binary classification

The ROC-AUC curves for the proposed BCNet model in binary classification at different magnifications, as shown in **Figure 4**, illustrated the model's exceptional performance in distinguishing between benign and malignant histopathology images. The model achieved an impressive ROC-AUC value of 0.996 at 40× magnification, demonstrating near-perfect classification accuracy at this lower magnification level. At 100× magnification, the model attained a flawless ROC-AUC value of 1.000, indicating perfect classification performance, where the model correctly identified all instances without error. For 200× magnification images, the model maintained a high level of accuracy with an ROC-AUC value of 0.972, showcasing its robustness and ability to handle increased image complexity. Finally, at 400× magnification, the ROC-AUC value was 0.994, reaffirming the model's high accuracy even at the highest magnification level. These consistently high ROC-AUC values across different magnifications underscore the BCNet model's reliability and effectiveness in the binary classification of breast cancer histopathology images, regardless of the magnification factor.

3.1.3 Confusion matrix for multi-class classifier

The confusion matrix for the BCNet model's multi-class classifier, as illustrated in **Figure 5**, provides a detailed breakdown of correctly classified samples across

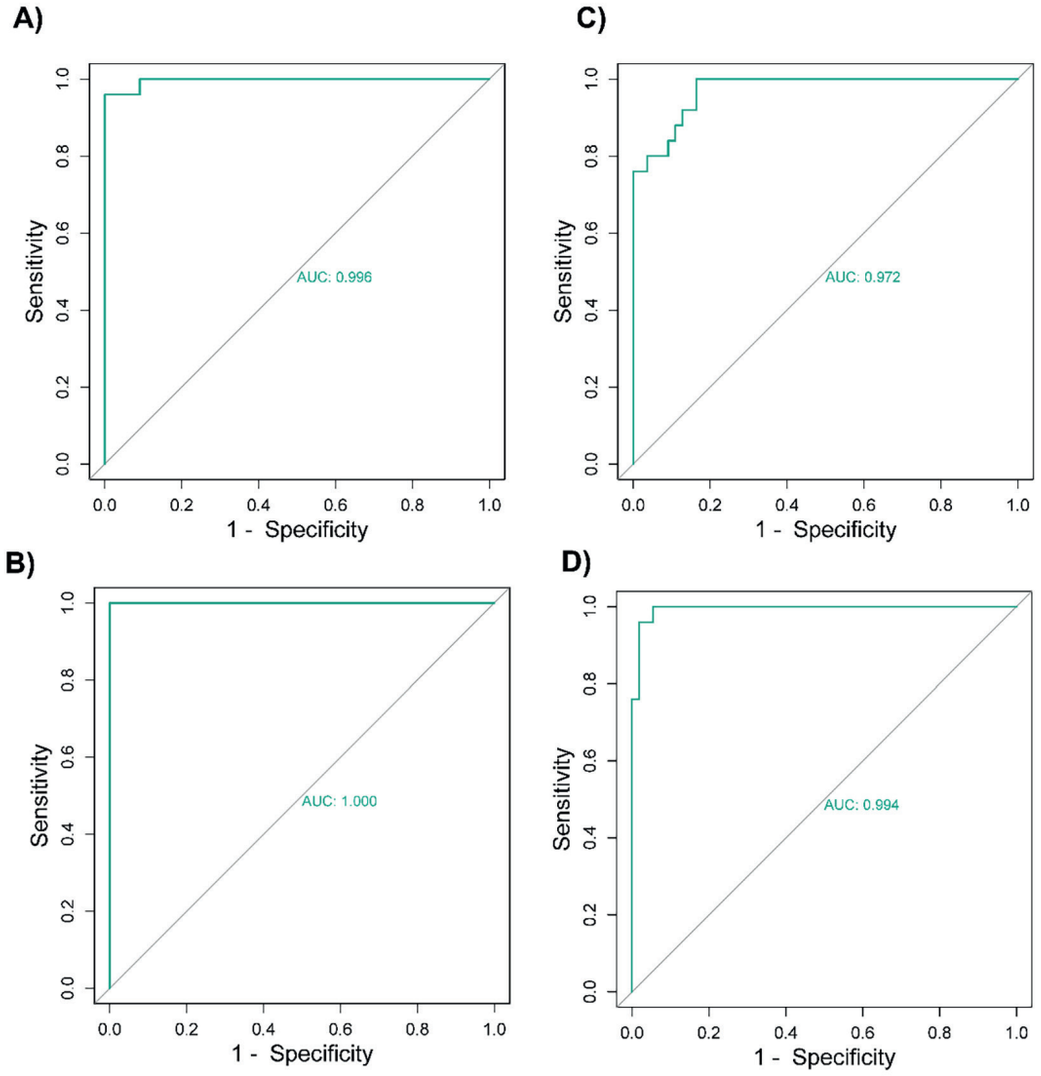

Figure 4.
ROC-AUC curves of the BCNet model for binary classification at different magnifications. The results are presented for histopathology images with magnification factors of 40× (A), 100× (B), 200× (C), and 400× (D).

different magnification levels. Specifically, the model correctly classified 614 out of 628 samples at 40× magnification, 878 out of 903 samples at 100× magnification, 765 out of 780 samples at 200× magnification, and 572 out of 600 samples at 400× magnification. These results highlight the model's high accuracy in distinguishing between the different classes in the dataset.

3.1.4 ROC-AUC curve analysis for the BCNet model in multi-class classification

The ROC-AUC curves for the BCNet model's multi-class classifier at different magnifications are illustrated in **Figure 6**. The performance of the model is assessed across four magnification levels: 40×, 100×, 200×, and 400×. Overall, the ROC-AUC curves across all magnifications illustrate the proposed model's excellent capability in multi-class classification, with consistently high AUC values that confirm the reliability and robustness of the classifier in distinguishing between various breast cancer histopathology image classes.

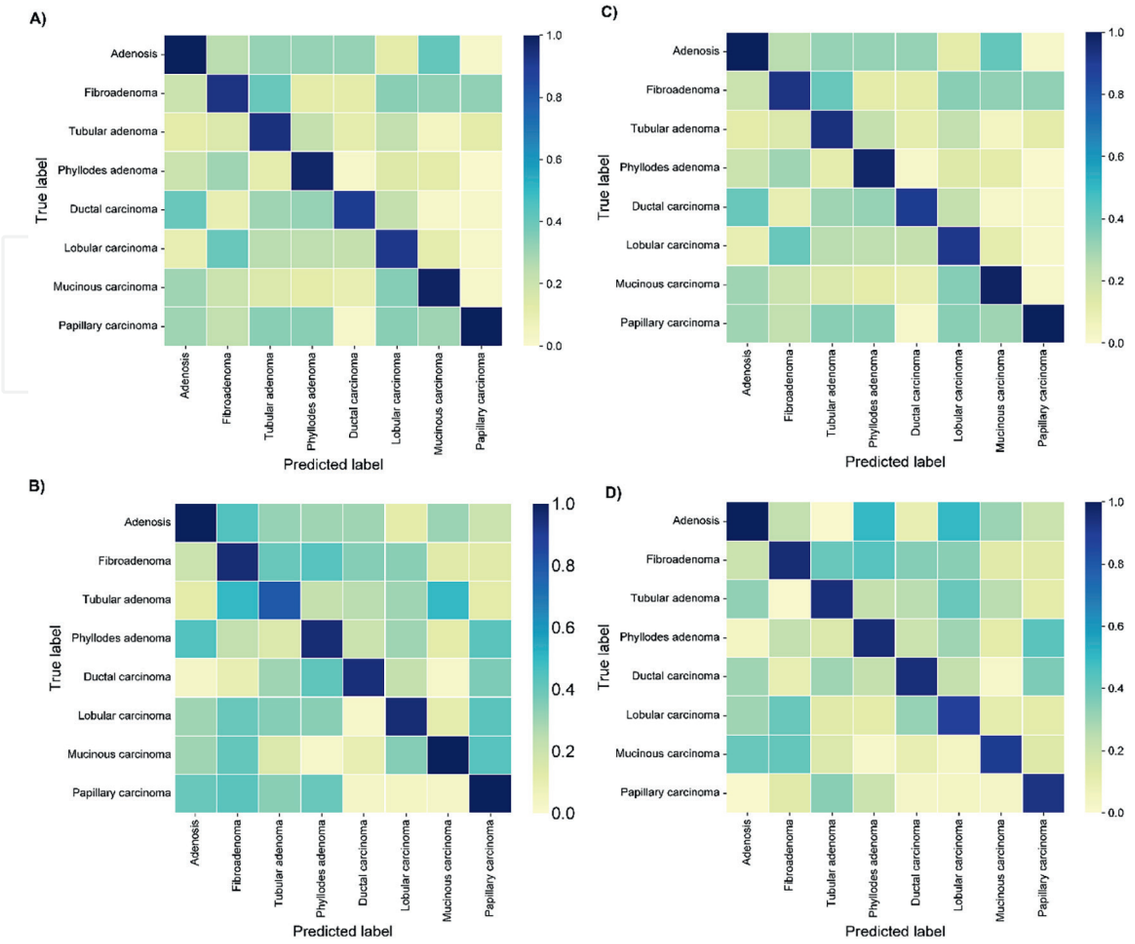

Figure 5.
Confusion matrix for the BCNet model's multi-class classifier at different magnification levels: 40× (A), 100× (B), 200× (C), and 400× (D).

4. Discussion

The findings from our study demonstrated the potential of our proposed BCNet model to enhance the accuracy and reliability of breast cancer detection and classification using histopathological images. BCNet has shown promising results by using CNN specifically tailored for the unique characteristics of breast tissue histopathology and surpassing the performance of existing state-of-the-art models in both binary and multi-class classification tasks. We expand on the integration of BCNet into clinical workflows, focusing on its role in assisting pathologists with decision-making to improve diagnostic accuracy and reduce workload.

The main contribution of this study is the development of BCNet, a 22-layer CNN model designed to manage the complexities of histopathological images, which often exhibit high variability due to differences in staining, magnification levels, and tissue morphology [20]. The architecture of BCNet, including its use of batch normalization, dropout, and Adam optimizer, has proven effective in reducing overfitting [40] and improving generalization across different magnification levels and tumor subtypes.

Our results indicate that BCNet achieves superior accuracy compared to pre-trained models such as VGG16 [20], VGG19 [20], Inception-V3 [11], DenseNet [38], and ResNet152 [32], which have traditionally been used through transfer learning.

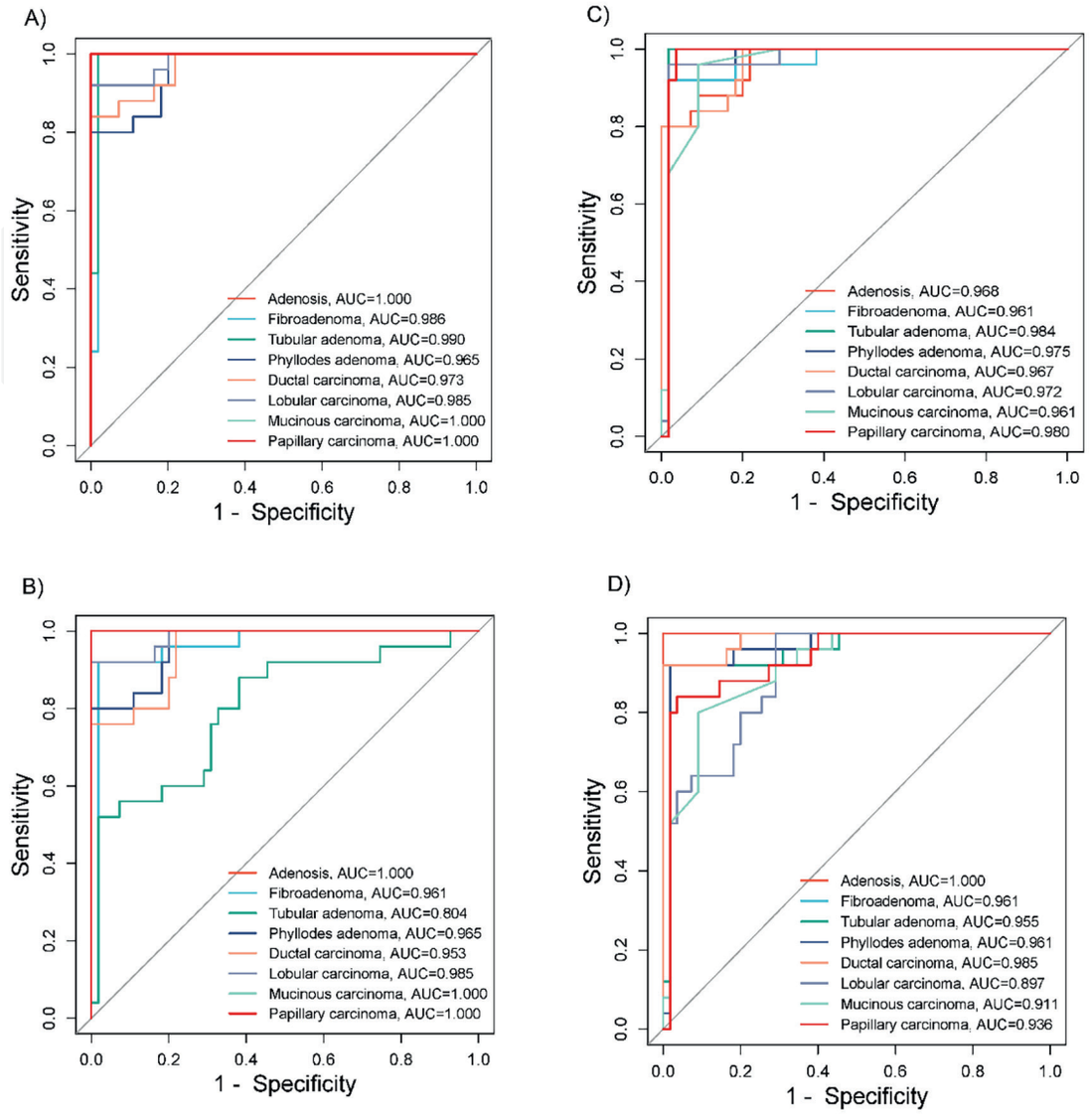

Figure 6.
ROC-AUC curves of the BCNet model in a multi-class classifier at different magnifications. The ROC-AUC results are shown for histopathology images with magnification factors of 40× (A), 100× (B), 200× (C), and 400× (D).

Despite transfer learning providing a strong starting point, it often suffers from limitations due to domain mismatch between the source domain of the pre-trained model and the target domain of histopathological images. In addition, our model also performed better than other combined models, such as the combination of ResNet50 and Inception module [41], and the CNN model with LSTM networks [10]. While transfer learning can provide a strong starting point, it often suffers from limitations due to domain mismatch between the pre-trained model's source domain and histopathological images [14]. In contrast, BCNet was designed and trained from scratch on the BreakHis dataset, allowing it to better capture the domain-specific features relevant to breast cancer histopathology.

In binary classification, BCNet achieved an accuracy of up to 99.8% at 100x magnification, demonstrating its robustness in distinguishing between benign and malignant tumors. This high level of accuracy is crucial for clinical applications, where early and precise diagnosis can significantly impact treatment decisions and patient outcomes, including the patient's recovery and survival [42]. For multi-class

classification, BCNet outperformed existing models such as a novel 6B-Net deep CNN model [43], achieving up to 99.6% accuracy at 200x magnification. This model performance is particularly important for pathologists, as it contributes to identifying specific subtypes of breast cancer, each of which may require different treatment approaches.

In addition to high accuracy metrics, the practical application of BCNet can be enhanced by integrating explainable AI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) [44], which provides a heatmap visualization to indicate the regions of histopathological images that contributed to the model's interpretability and transparency. This transparency allows health professionals to verify and trust the model's decisions, facilitating the model's integration into routine breast cancer diagnostics, particularly in settings with high pathologist workloads or limited expertise [44]. BCNet could be considered a valuable second opinion during routine screenings for early detection, ultimately improving patient outcomes. However, careful evaluation is necessary to integrate with existing clinical infrastructure. Potential challenges include compatibility with existing systems, clinicians' training requirements, and workflow adjustments for successful implementation.

Although the BreakHis dataset is widely accepted in breast cancer research, we acknowledge the potential risk of overfitting despite robust data augmentation techniques and the need for larger and more diverse datasets to address the concerns about the broader generalizability of our findings. To improve the BCNet generalizability, we performed data augmentation to artificially increase the size of the dataset using different techniques such as rotations, horizontal flipping, width and height shifts, shearing, zooming, and color normalization [45, 46]. Additionally, we plan to extend our model validation across multiple datasets and larger clinical samples. Although BCNet is currently focused on breast cancer diagnosis, its architecture is adaptable for other types of histopathological analysis.

Despite its future contributions, integrating BCNet into cancer diagnostics experienced several challenges, including ethical and legal concerns that must be addressed for responsible implementation. The ethical and legal concerns include: (1) Data privacy: The AI system's dependency on large datasets is exposed to patient data security and privacy-related risks. Our study utilized a dataset that is anonymized and secured to handle patient information through encryption to keep confidentiality and comply with data protection regulations such as the General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) [15]. (2) Algorithmic bias: AI models trained on biased datasets may exacerbate existing healthcare disparities. If trained predominantly on data from specific demographic groups, there is a risk of misdiagnosis or lower accuracy for minority populations, thus widening health inequalities and inequities [47]. We ensured that the BreakHis dataset was representative and bias mitigation strategies were applied throughout the development process [20]. Additionally, it covers a wide range of breast cancer subtypes through its huge collection of histopathological images [15]. (3) Diagnostic errors and accountability: Misdiagnoses or incorrect model predictions could have a detrimental effect on cancer care. It is necessary to establish a regulatory framework to ensure accountability in AI deployment in the healthcare system, including promoting transparency in decision-making processes using explainable AI (XAI) techniques [48, 49]. Furthermore, healthcare providers should supervise the use of BCNet, enhancing decision-making instead of replacing clinician decision-making [50]. Healthcare institutions should obtain informed consent from the patients to integrate the BCNet model into patient care. The other potential challenges might be

overcoming resistance from clinicians who are not familiar with AI and the potential for diagnostic errors if the model is not properly calibrated for varying clinical scenarios. The continual validation of the model is critical to ensure generalizability. Therefore, healthcare professionals should be trained on how to interpret and utilize AI results effectively [50].

While BCNet addresses some of the limitations of transfer learning, further research could explore hybrid approaches that combine transfer learning with domain-specific training to enhance model performance. Future research should also focus on clinical validation of BCNet across diverse clinical environments to facilitate integration into clinical workflows. Although this study focused on experimental validation using histopathological images, we are actively working toward collaborations with health institutions to test BCNet in real clinical settings. These efforts will help to evaluate its practicality, reliability, and adaptability, ensuring its performance is robust in real-world scenarios. The integration of BCNet into clinical workflows involves developing user-friendly interfaces and tools compatible with existing pathology systems, providing real-time, AI-assisted diagnostic support for pathologists. Additionally, the interpretability of the model's predictions remains an important area for future research. Finally, while our study focuses on breast cancer histopathology, the methodologies, and insights gained from developing BCNet could be adapted to other cancers and histopathological image analysis. This broader application has the potential to revolutionize cancer diagnostics and pave the way for more accurate, efficient, and accessible diagnostic tools across various medical domains.

5. Conclusion

Our newly developed BCNet represents a significant advancement in the field of breast cancer diagnostics. The BCNet model, specifically designed for breast cancer classification, demonstrated superior performance compared to existing state-of-the-art CNN models in both binary and multi-class classification tasks. These findings suggest that BCNet could significantly enhance diagnostic precision, reduce the burden on pathologists, and improve patient outcomes. Future studies should focus on validating BCNet across larger, more diverse datasets and integrating it into clinical practice to fully realize its potential in improving breast cancer diagnostics.

Conflict of interest

The authors declare no conflict of interest.

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