ISSN: 2093-5374 / E-ISSN: 2093-5382

Integrating Deep Learning Models and Data Augmentation Techniques for Improved Breast Cancer Detection

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Received: March 24, 2025; Revised: May 06, 2025; Accepted: June 07, 2025; Published: June 30, 2025

Abstract

Breast cancer (BC) is a prominent issue in global health that necessitates the utilization of progressively advanced diagnostic techniques to achieve early diagnosis and enhance patient outcomes. Patch-based histopathological images offer a deep insight into tissue structure and are crucial for accurately classifying benign and malignant breast tumours. Despite all the past work in this area, a helpful methodology is still lacking that connects different sources of data, amplifies the Input with various methods, and thoughtfully applies advanced deep-learning models to study these patches. We address BC detection here by working with various datasets, analyzing them in parallel at two magnifications (40X and 400X), and combining the results to explore better and diagnose the grouped tissues. A technique was employed to adapt data augmentation for the benign tumour class, addressing the issue of class imbalance. Every time, the DenseNet121 model predicted correctly at 40X, while the ResNet50V2 model was accurate when tested at 400X. When data at both magnifications is used in ResNet50, the model achieves a validation accuracy of 99.76%. They show that the best results are achieved when data from multiple sources and magnifications are consolidated. The model is made more general with augmentation, and pre-trained models play a part in detecting breast cancer (BC). Because it is more accurate, this style

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 2 (June), pp. 517-534. DOI: *10.58346/JOWUA.2025.I2.031*

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of testing enables patients to receive help when needed, thereby reducing the risk of unnecessary treatments.

Keywords: Breast Cancer Detection, Histopathological Image Analysis, Deep Learning, Patch-based Classification, Multi-Magnification Analysis, Data Augmentation.

1 Introduction

Uncontrolled cell growth often leads to the various types of cancer that occur in the body. These cells may induce nearby tissues to degrade, resulting in tumours that can metastasize to other parts of the body (Weinberg, 2007). Cancer may develop due to factors such as genetic issues, exposure to toxins, and personal lifestyle choices (Weinberg, 2007). It results in a lot of illness and death worldwide, so it must be thoroughly inspected and treated by doctors to find out the main reasons, design successful treatments and advocate for early identification (Tarver, 2012). One of the most common cancers to affect women all over the globe is breast cancer (BC). Many people can get this cancer, and it is often dangerous (Parise & Caggiano, 2016). There are malignant tumours in breast tissue that can cause cancer to spread and affect other areas (Alfonse et al., 2014). Young or old, rich or poor, BC does not show preference and may appear in any woman's life (Zhang, 2019). National BC Foundation estimates that in 2023, females in the USA will be diagnosed with about 297,790 new cases of invasive breast cancer (BC).

Furthermore, the last statistics showed that about 55,720 cases of non-invasive BC are expected. It is estimated that one woman faces breast cancer one time in every eight, throughout her life (National Breast Cancer Foundation, 2023). Because of this, it is necessary to focus on finding tumors early with advanced tools and procedures, since fast medical action can greatly affect a person’s survival and the success of the treatment (Basurto-Hurtado et al., 2022).

Traditional methods used for breast cancer (BC) diagnosis, such as mammography, ultrasound, and biopsy, have undoubtedly provided invaluable contributions to clinical practice (Mehta & Singh, 2025). Mammography, while valuable in breast disease detection, has limitations, including variable false negatives, reduced sensitivity in dense breast tissue, and a high false-positive rate (Dündar et al., 2006; Nakano et al., 2007). Ultrasound supplementation faces challenges, including false positives, increased costs, and limited resources, primarily due to the time-consuming nature of image interpretation. The proposed solutions encompass heightened clinical expertise, meticulous patient selection, and the integration of cutting-edge technologies, such as automated whole-breast ultrasound (Burkett & Hanemann, 2016). Breast biopsies are used to distinguish between benign and malignant tumours, but they are also costly and require a skilled person to perform them (Abel et al., 2012). MRI detects more things but is less accurate than mammography and ultrasound in telling tumours from healthy tissue (Wang, 2017). MRI has several drawbacks, including the generation of false positives, high expense, lengthy processing times, limited availability, and the need for specialized personnel. It is advised by health experts that any person with a BRCA mutation arranges yearly testing (Meaney et al., 2010).

To correctly diagnose cancer and inflammatory diseases, one must take a biopsy and investigate the sample using histopathology, since this process greatly helps patients recover (Aswathy & Jagannath, 2017). Expertise has for a long time been important for reading all types of images, including WSIs and histopathological images, in fields such as radiology and pathology. To diagnose the patient, the findings from microscopic examination of cell structures and their traits are used as signs of the disease. For instance, identifying aberrant cells with uncontrolled division (carcinomas) leads to cancer

diagnoses. Pathologists, armed with histopathological images, not only identify anomalies but also tailor treatment to each patient's unique condition, laying the foundation for precision medicine (Seo et al., 2022).

In the area of oncology, detection of breast cancer is vital, and the use of medical imaging along with AI has made a big difference in diagnostics (Basurto-Hurtado et al., 2022). If deep learning is applied to many labelled medical images, it can find abnormalities in the breast, tell apart lesions from normal cells, and help with radiologists' choices (Altayeb & Arabiat, 2024). By using computer-aided detection systems driven by advanced technologies, cases of breast cancer (BC) can be identified more accurately, thereby relieving doctors and nurses (Asiya & Sugitha, 2025).

Significant research has been conducted on BC detection, although there remains a strong need for further improvement in this area. Still missing is a binary classifier that can classify breast cancer images reliably as more magnification is used. The lack of good classifiers can sometimes result in mislabelling cancerous cells as non-cancerous, which is undesirable. There is also an issue because non-cancerous images in pathology datasets are far less common than cancerous images. Having fewer data points for the negative class poses a significant obstacle in creating accurate and dependable models for BC (Habeeb & Kazaz, 2023). Besides, there are cases where some image patches are erroneously labelled because tumour size, colour, shape, and the structure of the human body differ between them (Yadav et al., 2024). Addressing this mislabeling challenge necessitates the implementation of advanced preprocessing techniques.

Since the issues raised above are so serious, it becomes essential to set up a well-developed and smart breast cancer (BC) detection system to address them. It ought to increase classification accuracy at all magnification levels, tackle problems caused by an unequal dataset size, and utilize modern ways of preprocessing to reduce misclassifying images (Lei & Ibrahim, 2024). This study takes a stand on how binary classification of BC can be done with transfer learning using pre-trained neural models. The model developers drew pathology images from BC detection collections on Kaggle to solve the class imbalance problem and make the model more suitable for different cases. After that, data was augmented using various techniques. The results were assessed on datasets magnified 40X, 400X, and in a combination of 40X – 400X by calculating accuracy, precision, recall, F1-score, and analyzing the confusion matrix (Oblomurodov et al., 2024).

The main contributions of this study include:

1. We introduce innovative data augmentation techniques to address class imbalance, enhance model robustness, and improve generalization. These techniques involve creating balanced samples, introducing variations, optimizing feature learning, and maintaining image integrity during augmentation.
2. We integrate 40X and 400X magnification levels to enrich the dataset, broadening the scope of image characteristics models can learn from. This diversity enhances their generalization capabilities across a wide range of breast tissue scenarios.
3. We leveraged state-of-the-art transfer learning models, such as ResNe and DenseNet, to optimize training processes, enhance prediction accuracy, and unlock their potential for clinical applications in advancing breast cancer (BC) diagnosis.

2 Literature Review

Areesha et al. proposed their CBAM-VGGNet model as a new method for distinguishing H&E breast histopathological images in their first scholarly paper (Ijaz et al., 2023). For this stage, both VGG models are trained on malignant histology data related to the domain, then are tested using them as only static feature extractors. These models were trained before in advance on the ImageNet dataset. After the initial convolutional layer is applied, the model received a Global Average Pooling (GAP) layer as well as a Convolutional Block Attention Module (CBAM). Ensembles containing CBAM far outperform previous ways of solving the task in terms of accuracy and F1-score. The model appeared to offer a 98.96% level of accuracy and a 97.95% F1-score on images magnified 400X from the BreakHis dataset.

(Mudeng et al., 2023) suggested a special method that applies CNNs to automatically assess images, integrating well-trained InceptionResNetV2, InceptionV3, and NASNet-Large models, to group images in the BreaKHis dataset into different classes using 40X magnification. In the process, the researchers showed that a specially made deep ensemble system, trained using image-level labels, could successfully distinguish between benign and malignant cases in breast biopsies. This way of integrating models reaches an accuracy of 98%, which is better than both transformer-based and MLP-based methods by up to 20%. The research results clearly demonstrate that using both ensemble methods and transfer learning helps classification on small medical datasets.

A study that points out the significance of protecting confidential medical images came up with a cancer diagnosis system that combines federated learning and advanced learning techniques to ease and shorten the diagnosis (Peta & Koppu, 2023). The process consists of getting the image, securing the photo with the E-EIE technique, using the I-SCSO method to create keys, using the FLF system to keep the data safely, and using the C2T2 Net for disease identification. The process fine-tunes the model, lowering its loss score as a result of chaotic tuna swarm optimization (CTSO). Thanks to the BreakHis Database, the researchers achieve very impressive outcomes with an accuracy of 95.68%, recall of 95.6%, precision of 95.66%, F-measure of 95.63%, specificity of 95.6%, and kappa coefficient of 95.26%. The research offers a safe and effective solution for breast cancer diagnosis that makes use of automatic procedures, encryption, and federated learning to improve the results.

Also, (Demir, 2021) created an automated tool for recognize breast cancer (BC) in histopathological images. This study adds CLSTM networks and MWSA in the preprocessing stage as part of the investigation. The BreakHis dataset was used to train the CLSTM model, and this had a significant positive effect on the model's performance. The finetuning was done by changing the original CLSTM's softmax layer to an SVM classifier and using Bayesian optimization to gain optimal results. The accuracy of binary classification increased for all magnifications, by 13.04% at 40X, 11.78% at 100X, 0.49% at 200X, and 12.36% at 400X. Between 48.14% and 57% of improvement in performance was seen in the eight-class classification model.

Lack of proper knowledge about breast cancer among the public often leads to its diagnosis at later stages, showing why it's important to detect it as soon as possible. Aljuaid et al. came up with a computer-aided diagnostic system using ResNet-18, ShuffleNet, and Inception-V3 deep neural networks and trained them using transfer learning to increase detection and classification speed. Using the results from the BreakHis dataset, the ResNet model reached an accuracy of 99.7%, Inception-V3 got 97.66%, and ShuffleNet achieved 96.94% precision in telling apart benign cases from malignant ones. ResNet achieved average accuracy of 97.81%, Inception-V3 attained 96.07%, and ShuffleNet had an average accuracy of 95.79% for multiclass classification. The suggested technique leads to

possible improvements in early BC detection and organization, and it supports less experienced healthcare workers in providing better care.

The authors featured in the paper (Umer et al., 2022) develop a special 6B-Net with deep CNN features that also include a feature fusion and selection component. Among the data were a BreaKHis set (with 7,909 photos in 8 classes) and a breast cancer histopathology dataset (3,771 photos in 4 classes). With the proposed approach, the average accuracy for four classes of breast cancer is 94.20%, and it is 90.10% for eight classes. With its potential for determining early cancer and accurate classification, these results back up tools that aid pathologists in their struggle with breast cancer. Tummala and associates (Tummala et al., 2022) note that using histopathology images can significantly enhance the ability to detect this tumour type. Researchers investigate whether an ensemble of Swin Transformers (SwinTs), a type of vision transformer, can achieve good performance in BC classification on the BreaKHis dataset. The group of SwinTs shows excellent results, reaching an average accuracy of 96.0% for multiclass tasks and 99.6% for tasks with only two classes. They show that SwinTs can improve past efforts at detecting different breast cancer subtypes from pathological images and possibly alleviate the burden on pathologists. In addition, a study (Singh & Kumar, 2022) revealed a neural network approach that includes inception and residual blocks for breast cancer (BC) detection in histopathology. BIOII-NBI researchers applied their model to BHI and BreakHis datasets and managed to achieve 96.42% accuracy when training on BreakHis and 80.17% when training on BHI. The results of the model are very good at different magnifications. Accuracy of the BHI on BreakHis is 85.21%, while for magnification levels 40X, 100X, 200X, and 400X, the scores are 80.80%, 82.76%, 86.55%, and 85.80%, accordingly.

In response to the pressing global issue of BC, particularly among women lacking awareness and diagnostic accessibility, a study (Patel et al., 2023) unveils GARL-Net, a novel approach for significantly improving breast cancer classification accuracy. GARL-Net integrates transfer learning with DenseNet121, fine-tuning, and an adaptive complement cross-entropy loss function. This innovative strategy also incorporates adaptive regularization and complement entropy techniques. Notably, GARL-Net surpasses existing methods, achieving remarkable results, including 99.49% accuracy in binary breast cancer (BC) classification on the BreakHis dataset. This research underscores the potential to revolutionize BC diagnosis, ultimately contributing to saving lives through precise and efficient classification.

3 Methodology

3.1. Study Approach

BreakHis (Sudharshan et al., 2019) was chosen to classify Bias Checking for Breast Cancer Histopathological Images in the first stage. The collection of data in this dataset has very good quality and includes detailed annotations of histopathological images from breast cancer samples. With a detailed summary of BC categories, the data set is extremely useful for arranging and diagnosing breast cancer.

3.2. Study Sample

The images for the study are from 82 patients, showing both benign as well as malignant breast tumours at magnifications 40X, 100X, 200X, and 400X, working well with binary class and multiclass classification scenarios (Figure 1). Because the dataset is annotated, using it is much easier and takes a lot less time for preparation. Among the information added in these annotations are the kind of tumor

(not just benign or malignant), specific features of the tumor's structure, and any other important things.

3.3. Applied Techniques

This approach makes use of transfer learning and ensemble techniques, which help us spot blood clots more accurately at all magnification stages and eventually support early diagnosis and better care for our patients.

4 Results

Microscopic images (9,109) of breast tumour tissues taken from 82 patients at various magnitudes were studied. This dataset has 2,480 benign samples and 5,429 malignant images with 8-bit values for each color and a size of 3-channel RGB 700X460-pixel PNG files. The data was got by performing SOB surgery in Paraná, Brazil at the P&D Laboratory, Pathological Anatomy, and Cytopathology.

The data was gathered from (Wang et al., 2021) and covers 7,909 pictures of breast tumour tissue seen in microscopes. The images were made with different levels of magnification, like 40X, 100X, 200X, and 400X, as you see in Figure 1. They were changed to have 224x224 pixels and arranged to be used in both binary and multiclass classifications. In this study, we focused on binary class classification, specifically two magnification levels: 40X and 400X. This was to enhance the robustness of our analysis, a critical step in merging the datasets that combine benign and malignant samples from both magnification levels **(Figure 2**). This integration ensures a more comprehensive dataset for training and testing. **Table 1** provides the dataset distribution, highlighting a substantial presence of malignant tumour images compared to benign ones. To address the class imbalance, data augmentation is exclusively applied to benign tumour images, ensuring an equal ratio of training and testing images and thereby enhancing the accuracy of binary cancer classification.

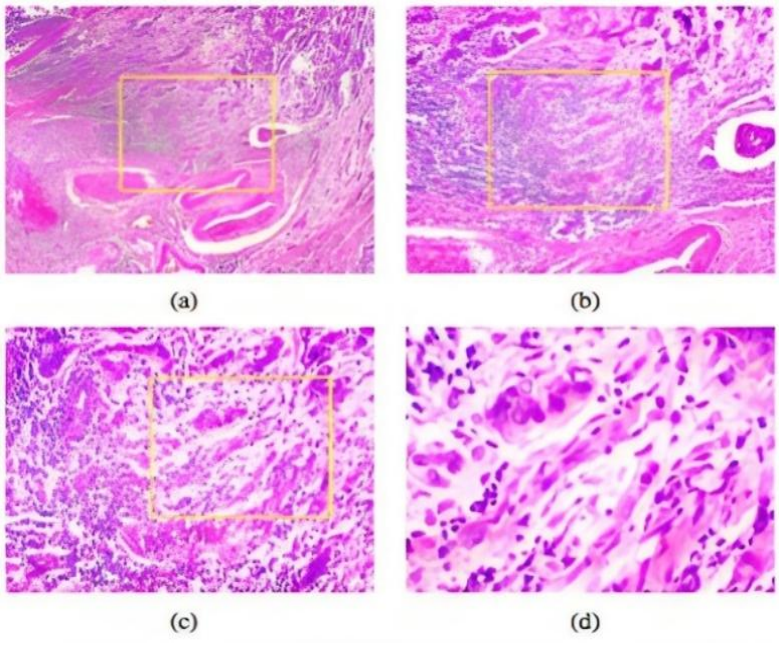

Figure 1: Malignant Tumour with Different Magnification Factors: (a) 40X, (b) 100X, (c) 200X, and (d) 400X

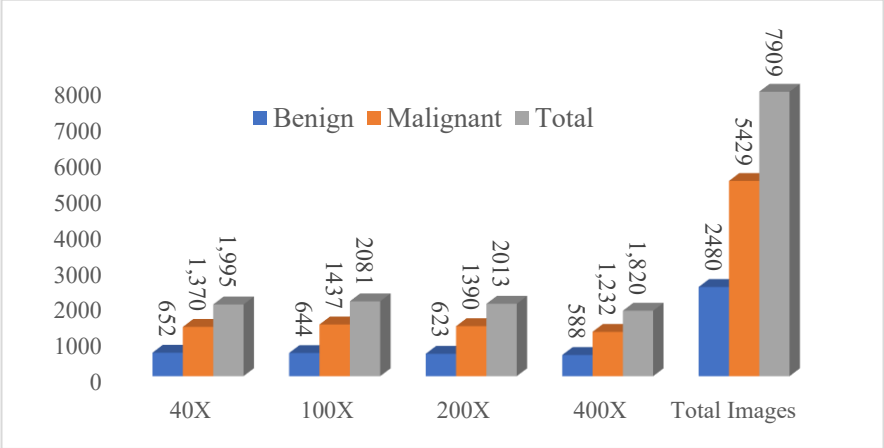

Figure 2: Tumor Analysis using Different Magnification Levels

Table 1: The Data Augmentation for Cancerous Classes

Magnification Level	Benign	Malignant	Total
40X	652	1,370	1,995
400X	588	1,232	1,820
40X + 400X	1240	2602	3842
Data Augmentation (Benign)	2602	2602	5204

Data augmentation is a crucial component in enhancing the robustness and performance of the breast cancer classification model. Given the inherent class imbalance in our dataset, we focus our augmentation (Agbley et al., 2022) efforts exclusively on benign tumour images to ensure a balanced representation. A range of random image transformation techniques was applied, including 20-degree image rotation, a 10% actual image width shift, a 10% height shift, a 20-degree shear, a 20% image zoom, and enabling horizontal flipping. Additionally, we employ a fill mode of the nearest pixel value to maintain the image quality mentioned in **Table 2**.

Table 2: Data Augmentation

Augmentation Parameter	Value
Rotation	20 degrees
Width Shift	10%
Height Shift	10%
Shear	20 degrees
Zoom	20%
Horizontal Flip	Enabled (True)
Fill Mode	Nearest pixel value(fill_mode='nearest')

After data augmentation and preprocessing, we develop a medical image analysis model by partitioning the dataset into training, validation, and testing subsets, as mentioned in **Table 3**. The dataset includes two magnification levels, 40X and 400X, as well as a merged 40X + 400X dataset, thereby enhancing model comprehensiveness. For 40X magnification, approximately 80% of the images were used for training, 9% for validation, and 10% for testing, totalling around 2,740 images. Similarly, for 400X magnification, approximately 80% of the data was allocated for training, 7% for validation, and 8% for testing, resulting in around 2,464 images. In the merged dataset, about 80% is designated for training, 9% for validation, and 10% for testing, resulting in approximately 5,204

images. This distribution ensures balanced representation across magnification levels, facilitating precise evaluation and assessment of the model.

Table 3: Dataset Distribution

	Training Dataset	Validation Dataset	Testing Dataset	Total
40X	2243	247	250	2740
400X	2130	173	161	2464
40X + 400X	4308	469	427	5204

Leverages the fundamental concept of transfer learning (Li et al., 2020) (Bardou et al., 2018) in deep learning, a technique that accelerates model development by capitalizing on existing knowledge acquired from solving related problems. This method conserves time and computational resources while also leveraging the power of pre-trained models, which were initially trained on extensive datasets such as ImageNet. These models are adapted for specialized tasks to enhance the performance of the target model. We further employed three pre-trained architectures: DenseNet-121, ResNet-50V2, and ResNet-50. The proposed methodology for the ResNet50 model is trained on the combined dataset (**Figure 3)**. The same methodology was used for 40X and 400X, along with their corresponding models.

ImageNet, a comprehensive image database comprising millions of labelled images across numerous object categories, plays a vital role in the realms of deep learning and computer vision, setting the standard for training and evaluating deep neural networks (DNNs) in image classification and object detection tasks (Yamlome et al., 2020).

Global Average Pooling (GAP) Layer

The inclusion of the GAP layer is a vital aspect of NN architecture (Mudeng et al., 2023). The GAP operation is performed once the convolutional layers have completed their task of extracting unique characteristics from the input images. By computing the average value of each feature map, this layer reduces the spatial dimensions of the maps to a single numerical number. This strategy accomplishes two goals simultaneously: it reduces the total number of training parameters used in the model and introduces a spatial hierarchy to the modelled features.

Dropout Layer

Dropout is a valuable technique we employ to enhance our models' ability to generalize and avoid overfitting (Gupta & Chawla, 2020). During the training process, the dropout feature randomly deactivates some of the input units by resetting their values to zero. As a result, the network can discover a larger number of stable features, which lowers the risk of it depending too much on a single type of Input. This prevents the model from only remembering what it learned during training and enables it to detect functional patterns, which is crucial for large datasets.

Batch Normalization

Batch Normalisation plays a significant role in how neural network architectures function. With it, each layer's activations tend to normalize evenly over mini-batches, which helps decrease the amount of internal covariate shift. A covariate shift happens when the input data in an NN becomes uneven as you train, which makes it less likely for the NN to learn correctly. As a result, models are trained more systematically and quickly, and they are also less likely to fail or get stuck since learning rates can be

increased. Ensuring the training process runs smoothly and reliably depends mainly on this key aspect (Abel et al., 2012).

Dense Layers

Our NN would not work well without dense layers. Another name for these layers is dense layers, as they form direct connections between every neuron in the above and below levels. They enable the network to identify and track intricate relationships within the information. It serves to connect what the model has learned and what it will take as its final decision.

Activation Function Sigmoid

In the output layer of our model, we employ the sigmoid activation function. This choice is beneficial for tasks like breast cancer diagnosis, which involve binary classification. The Sigmoid function compresses the model's raw output into a range between 0 and 1. This range can interpreted as the probability that a sample belongs to either the positive class (malignant) or the negative class (benign). This activation function is ideal for this binary classification task as it produces straightforward probability scores that are easy to understand (Demir, 2021).

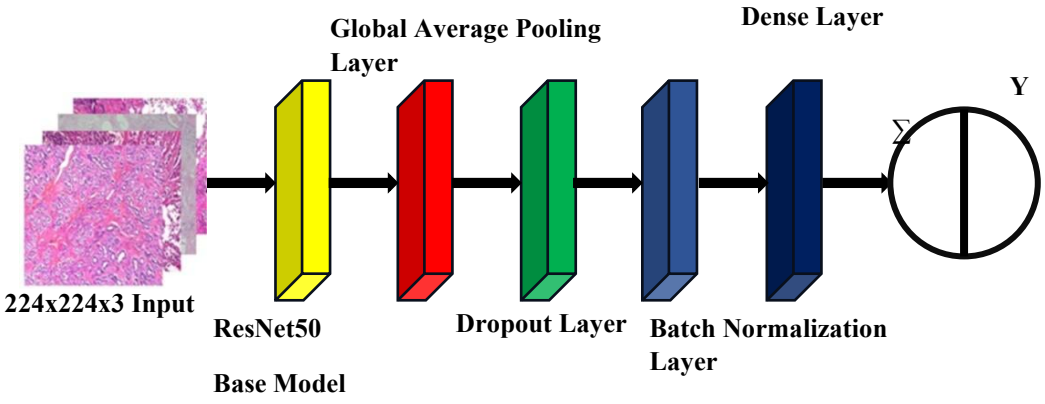

Figure 3: Schematic of the Resnet50-Based Feature Extraction Process

DenseNet121 is trained on the 40X dataset, while ResNet50V2 focuses on the 400X magnification level, and ResNet50 utilizes the combined 40X and 400X databases. DenseNet is a densely connected layers-based CNN architecture. It differs from traditional architectures in that it connects each layer to the subsequent layer in a feed-forward manner. This dense connectivity enhances feature reuse and promotes gradient flow, making the network more efficient and robust (Yu et al., 2023). ResNet50 is a specific variant of the ResNet architecture, consisting of 50 layers, with applications in image classification, segmentation, and object detection. It utilizes residual blocks for training highly complex neural networks (Wang et al., 2021). ResNet50V2 is a variant of the ResNet (Residual Network) architecture. It leads to various improvements, including the use of bottleneck blocks and the ReLU (Rectified Linear Unit) activation function. These enhancements result in a deeper and more efficient network while mitigating the vanishing gradient problem. These models, along with their corresponding datasets, synergize features from both magnification levels, thereby boosting classification accuracy. Detailed block diagrams of the 40X, 400X, and 40X + 400X datasets, including the data augmentation technique and their corresponding trained models, are given in **Figures 4,5 and 6.**

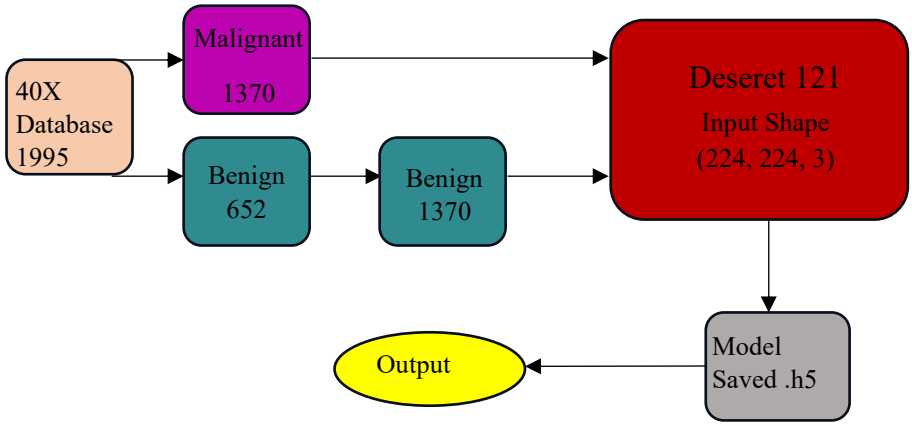

Figure 4: Data Augmentation Flow for a 40x Magnification Dataset

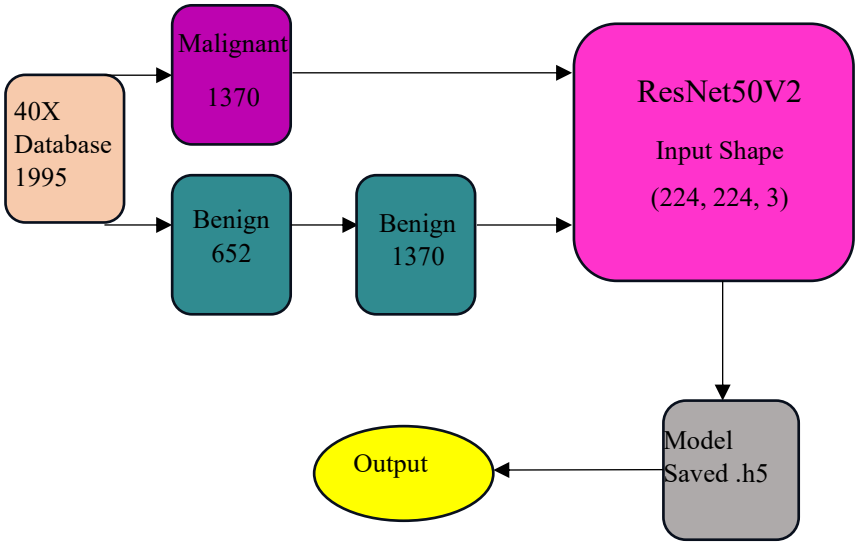

Figure 5: Data Augmentation Flow for a 400x Magnification Dataset

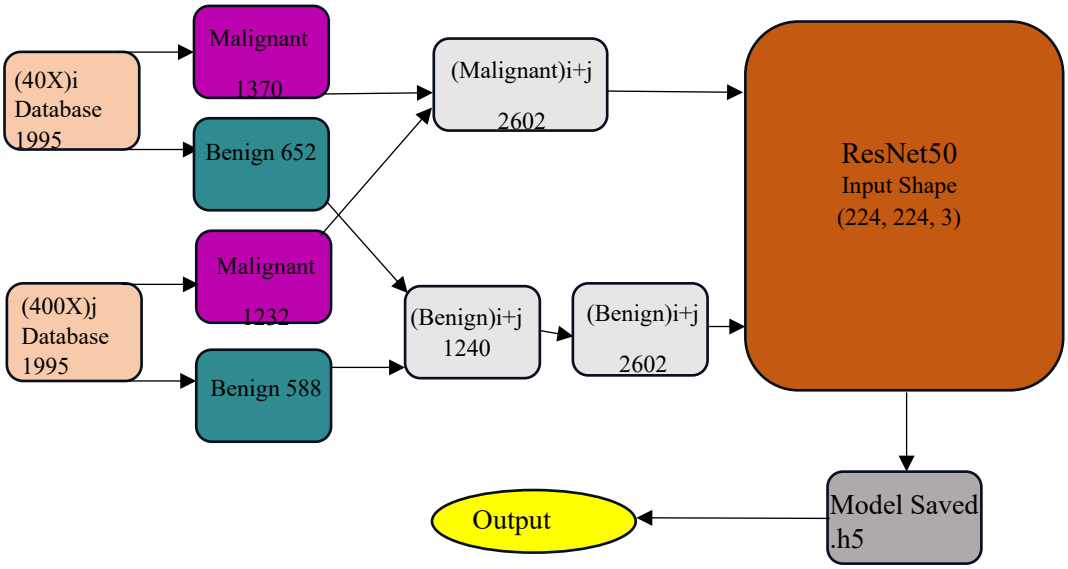

Figure 6: Data Augmentation Flow for a 40x + 400x Magnification Dataset

Our evaluations of the models were done by using famous scoring techniques after our training process had completed on each set of data. They include precision and recall, which show the accuracy of recognizing the right cases and discovering all cases that should be found. By calculating the F1 score, you compare the precision and recall to find a result. When data is not evenly spread, the harmonization steps really help. How accurate the model is can be determined by running it in several different situations. To check the results, we used confusion matrices. This way of looking at things labels results as true positives, true negatives, false positives, and false negatives. Looking at these topics helps identify the strengths and weaknesses of the model. Through this process, the model that is both reliable and exact for breast cancer classification can be chosen and perfected.

5 Discussion

We outline a robust process for detecting breast cancer that addresses challenges such as poor classification accuracy, data imbalance, and mislabeled images—utilizing transfer learning and combining multiple techniques. The goal of our approach was to accurately and reliably detect breast cancer at all magnifications, which contributed to early detection and improved patient care. Because there were many breast cancer patient cases with various magnifications, BreakHis was chosen as it fits both classification tasks. We merge the 40X and 400X datasets, combining benign and malignant samples from both magnification levels to address data imbalance and enhance the robustness of the analysis. The data augmentation technique, which incorporates a range of image transformations, including rotation, shifts, shear, zoom, and flipping, was used to equalize the ratio of benign and malignant classes for model training. Each transformation introduces a level of unpredictability into the training data, strategically addressing the class imbalance challenge while stimulating the model's capacity to detect benign cases. This augmentation strategy proves to be a crucial approach, offering numerous advantages. After preparing the complete binary class classification dataset, it was split into 80% training, 10% validation, and the remaining 10% reserved for model testing.

Additionally, our approach involves the careful selection of models tailored to specific datasets. Four experiments are done, where DenseNet121 works for the 40X dataset, ResNet50V2 at 400X magnification, and ResNet50 is assigned for all datasets together. Choosing the model is careful, done based on the features and goals of every set of data, thus making them work best at finding key patterns. Using various microscopes with various magnifications helps our approach.

Table 4 represents how well the models performed, giving meaningful proof of our transfer learning strategy.

Table 4: Pre-Trained Models Evaluation

	Training Accuracy	**Training Loss**	**Validation Accuracy**	**Validation Loss**	**Testing Accuracy**
DenseNet121 (40X)	0.9991	0.0085	0.9960	0.0475	1.00
ResNet50V2 (400X)	0.9953	0.0212	0.9942	0.0230	1.00
ResNet50 (40X + 400X)	0.9979	0.0085	0.9936	0.0256	0.9976

The training and validation accuracies recorded by DenseNet121 are 99.91% and 99.60%, which indicates that it is excellent at working with complex data. His task remained difficult; yet, under the highest magnification setting, ResNet50V2 did exceptionally well by reaching training and validation accuracies of 99.53% and 99.42%, respectively. The model showed excellent results during training

and validation, getting 99.79% and 99.36% accuracy, respectively. From these accuracy metrics, we can say that transfer learning did well in our study, making it clear that the models were able to transfer what they learned and adapt properly to new datasets. For benign tumours, DenseNet121 and ResNet50V2 showed accuracy of 100% in their classification report (Table 5). Therefore, the methods were efficient at finding the differences between benign and malignant breast tumours at lower magnification. Strong numbers for precision, recall, and F1-score in the models suggest that the identification of benign cases includes very few errors. The results show that all three neural network models reached 100% accuracy and did not make mistakes during the malignant tumour classification. This result proves that such a device can find cancerous tissue very accurately. Thanks to the ensemble's notable performance, detecting cancerous tumours could be done confidently. On the whole, the results revealed in Table 5 demonstrate that the suggested approach gives trustworthy and precise results for all magnification levels. Thanks to this approach, early detection of breast cancer helps doctors better manage their patients. Superior results for both kinds of cases (benign and malignant) are observed throughout the methodology's application.

Table 5: Classification Report for Proposed Models

	Models	Accuracy	Precision	Recall	F1 - Score
Benign	DenseNet121 (40X)	1.00	1.00	1.00	1.00
	ResNet50V2 (400X)	1.00	1.00	1.00	1.00
	ResNet50 (40X + 400X)	1.00	1.00	1.00	1.00
Malignant	DenseNet121 (40X)	1.00	1.00	1.00	1.00
	ResNet50V2 (400X)	1.00	1.00	1.00	1.00
	ResNet50 (40X + 400X)	1.00	1.00	1.00	1.00

Additionally, confusion matrices assess the model's performance in identifying tumours as benign or malignant in various situations and model configurations. DenseNet121 was entirely accurate in determining if a case was benign or malignant for all 131 benign and 119 malignant test cases. It implies that the model is reliable and accurate in distinguishing between different types of tumours by examining samples under a microscope at 40X power. ResNet50V2 performed very well in the confusion matrix, accurately categorizing all samples as either benign or malignant. The model correctly discovered and arranged images of both benign and malignant tumours in the 400X dataset. The ResNet50 model was found to be robust because it correctly identified 210 standard samples and 216 cases of cancer development. The model was incorrect in one case, judging a harmless tissue slide as suspicious of cancer. Although an uncommon situation, this scenario suggests that combining 40X and 400X data helps achieve fewer misclassifications.

From the details in the confusion matrices displayed in Figure 7, we see that both DenseNet121 and ResNet50V2 produced no examples of false positives or false negatives. The various models consistently demonstrated strong skills in distinguishing between regular tumours and cancerous ones. ResNet50 is noteworthy because it made only one wrong classification. This model made a few incorrect classifications when working with data from the 40X and 400X datasets despite a minimal error rate. Combining data from multiple magnifications adds some difficulty to the classification, but

not significantly. It highlights the fact that achieving great accuracy in such ensemble models is possible with proper handling.

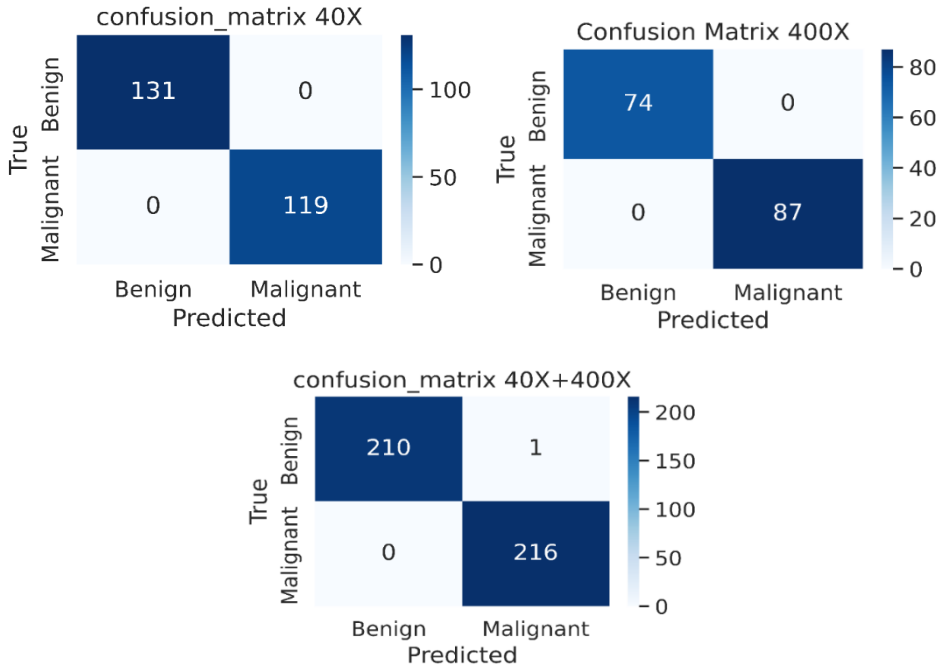

Figure 7: Confusion Matrix for the 40x, 400x, and 40+400 Magnification

6 Conclusion

In short, our research facilitates the accurate categorization of breast cancer images at various magnifications. We addressed challenges related to accuracy, data imbalance, and mislabeled images using a comprehensive approach. With transfer learning and advanced models (DenseNet121 for 40X, ResNet50V2 for 400X, and ResNet50 for both 40X and 400X datasets), impressive results were obtained. The training and validation accuracy was very high, and our models were able to accurately recognize benign and malignant tumours. By utilizing various methods to enhance the data and employing multiple zoom levels, models have significantly improved their applicability in new settings and scenarios. Also, the chosen technique helped to prevent misclassifications and resulted in a highly accurate detection of breast cancer. Our approach shows great potential for catching breast cancer early and accurately, which supports better outcomes for those who receive treatment. Intelligent and reliable systems for detecting breast cancer can be developed by combining transfer learning, strategic data augmentation, and careful model selection.

Limitations of the Study

Our work offers a strong way to detect breast cancer, though there are some limitations we should be aware of. Some of these issues involve getting access to the data, its quality, how different models can be used with a variety of datasets, clinical validation, and the way doctors grasp the model. Before using the system in hospitals, class imbalance and thoughts on ethics and regulation need to be considered. The results of research are meant to connect the method with current imaging methods, so machine learning can be used more dependably and updated constantly.

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