APPLICATION OF NEURAL NETWORKS IN SILICONE BREAST IMPLANT DIAGNOSTICS ON MAGNETIC RESONANCE IMAGING

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Abstract

Breast augmentation is one of the most frequently performed cosmetic procedures worldwide, but it carries certain risks including breast implant rupture. Timely and accurate diagnostics of ruptures are crucial, as undiagnosed ruptures can lead to serious health complications. Imaging methods, such as magnetic resonance imaging (MRI), are recommended for the diagnosis of breast implants due to their high accuracy. However, current diagnostics rely heavily on the subjective interpretation and experience of the physician. This study investigates the potential of neural networks (NN) to address this limitation and improve the accuracy of rupture detection in silicone breast implants. We applied a deep learning-based neural network system trained on MRI images of breast implants to detect ruptures. The dataset included annotated MRI scans of symptomatic and asymptomatic patients with confirmed implant integrity or rupture. Several models were trained using ResNet-18, ResNet-50, and Xception networks, with various hyperparameter settings and augmentation techniques applied to enhance model performance and generalizability. The performance of the NN model was evaluated using confusion matrices and standard metrics such as true positive rate (TPR) and true negative rate (TNR). A semi-automated algorithm for the detection of intracapsular ruptures of breast implants on MRI was successfully developed. The algorithm correctly detected ruptures in 95.4% of cases and accurately identified cases without rupture in 86.7% of instances. Our findings highlight the potential of neural networks as a supportive tool in diagnosing breast implant ruptures. By semi-automating rupture detection, NNs can reduce diagnostic errors, expedite image evaluation, and optimize resource use in medical practice. The study underscores the importance of combining artificial intelligence with expert evaluation to enhance patient care and reduce costs in medical diagnostics.

Keywords

breast implant, magnetic resonance, rupture, neural network

Introduction

Currently, breast augmentation is an increasingly popular trend. It is a cosmetic procedure performed for aesthetic or medical reasons with more than 1.6 million surgeries performed worldwide [1].

However, there are potential complications that can occur in the life of a patient with breast implant. Complications include capsular contracture, anaplastic large cell lymphoma associated with the breast implant, and rupture. One frequently mentioned complication is implant rupture, which can be extracapsular or intracapsular. Rupture can occur due to iatrogenic damage (during surgery) or mechanical damage (e.g. trauma) [2, 3].

A clinical examination of the patient is necessary to diagnose possible complications after breast augmentation. However, clinical examination is only sometimes sufficient to make an accurate diagnosis. Currently, imaging modalities are used in clinical practice to diagnose implant rupture [4, 5]. Diagnosis after plastic surgery can be performed using imaging modalities such as mammography, ultrasound (US), magnetic resonance imaging (MRI), or a combination of these.

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In the event of an implant rupture, early diagnosis of the patient is essential, as the condition resulting from this defect can be life-threatening. Lotan points out that the prevalence of implant rupture varies widely but can be as high as 77% depending on the type of implant, its longevity and other factors [6]. This issue is also confirmed by Samreen in his study, with somewhat different prevalence values, stating 55%. [7]. Brown in his research points out factors affecting the incidence of implant rupture, such as the age of the implant (median 10.8 years) and its location (subglandular, submuscular) [8].

Internationally recognized authorities are also calling for this serious issue to be addressed. For example, the U.S. Food and Drug Administration (FDA) recommends that women with breast implants be screened with MRI starting three years after implantation, with regular follow-up exams every two years [2, 9].

The approach to this issue is still very conservative in the Czech Republic. There is currently no standardised procedure or recommendation for screening women with breast implants. In general, the first step in the diagnosis of possible defects is a clinical examination by a physician, but this may not be sufficient and should be supplemented by appropriate imaging methods [8].

While current methods such as US and MRI are commonly used in clinical practice to diagnose breast implant rupture, there are still limitations in terms of accuracy and the time-consuming nature of the examinations. Imaging methods rely on expert interpretation of MRI images by radiologists, where the human factor can play a role in the assessment. In this context, the use of deep learning (DL) is a promising tool that could pre-process images with limited expert time demands.

The aim of this study is to propose a neural network (NN)-based algorithm capable of semi-automatically detecting breast implant rupture from MRI images. The ability of neural networks to analyse large amounts of data and detect subtle structural abnormalities that may escape the human eye is expected to improve diagnostic accuracy, minimize the risk of false-negative or false-positive results. In addition, semi-automated diagnosis using NN could significantly reduce the time needed for image interpretation and serve as a support tool for physicians, acting as a "second reading". Research in this area is therefore essential to ensure better patient care and to optimize costs and resources in medical practice.

Methods

This paper proposes an algorithm for the semi-automatic detection of intracapsular ruptures based on axial MRI T2 STIR WS (Short Tau Inversion Recovery Water Suppression) images. The algorithm is based on the use of neural networks in the Matlab2019b environment (The MathWorks, Inc., USA). The goal is to detect the position of the rupture based on the classification of individual pixels.

Dataset

In this study, anonymized data from patients with and without intracapsular breast implant ruptures were used. Fully anonymized data were provided by the Clinic of Radiology and Nuclear Medicine at the University Hospital Královské Vinohrady, 3rd Faculty of Medicine, Charles University. The study was approved by Ethical Review Board University Hospital Královské Vinohrady (EK-R/02/0/2021). The provided dataset consisted of 30 patients. The examinations were conducted using a 1.5 T MRI scanners Signa (GE HealthCare, Boston, Massachusetts, USA) and Magnetom Sola (Siemens Healthineers, Erlangen, Germany). For subsequent data processing, the axial T2 STIR water suppression sequence was used, as it suppresses the fat signal and water, which facilitates the detection of intracapsular ruptures. The images were provided in DICOM format and later converted to jpg format for further processing. Annotation was then performed by a radiologist using the software LabelImg [10] (Fig. 1).

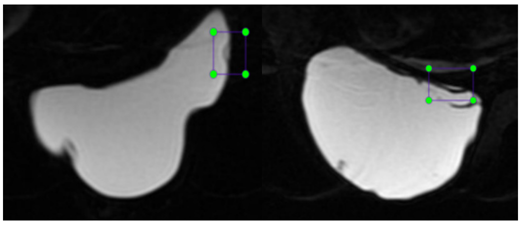

Fig. 1: Annotation of intracapsular ruptures in the LabelIng software by a radiologist.

The image histograms were further normalized.

Based on the entire set of patients, the data was split into training, validation, and test sets in a ratio of 15/10/5. The data were divided according to the number of patients. This data split provided sufficient distribution for model optimization and testing on an independent dataset.

Network architecture

A pre-trained neural network was used to detect intracapsular breast implant ruptures. We utilized the pre-trained networks ResNet-18 (Fig. 2), ResNet-50 (Fig. 3) and Xception (Fig. 4) to compare their performance. These pre-trained networks are most suitable for tasks involving image segmentation and classification with smaller datasets, having been trained on a large number of images from the ImageNet database. The network's performance was also tested with different image sizes, specifically 299×299 and 500×500.

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Table 1: Hyperparameter settings.

Model	NN	Image Size (pixel)	Solver	Epoch (-)	Mini batch (-)	Frequency (-)
Model 38Xc	Xception	299×299	adam	50	32	30
Model 2Xa	Resnet-18	500×500	sgdm	15	16	10
Model 5	Resnet-50	500×500	sgdm	10	16	10

Table 2: Data augmentation for each model.

Model	NN	Augmenter rotation	Augmenter X (pixel)	Augmenter Y (pixel)
Model 38Xc	Xception	-180;180	-10;10	-10;10
Model 2Xa	Resnet-18	-180;180	-50;50	-50;50
Model 5	Resnet-50	-180;180	-50;50	-50;50

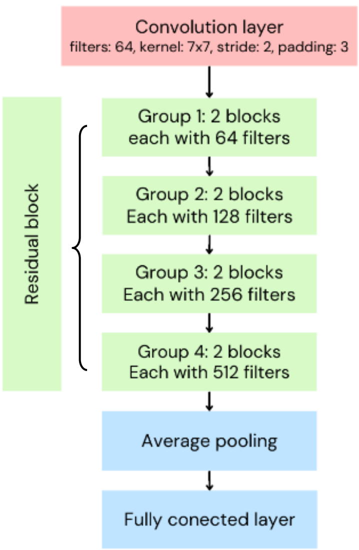

Fig. 2: Block diagram of NN ResNet-18 architecture.

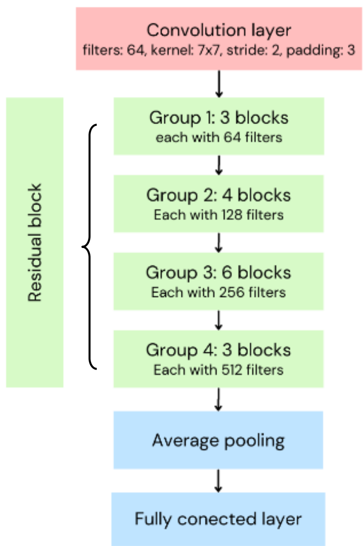

Fig. 3: Block diagram of NN ResNet-50 architecture.

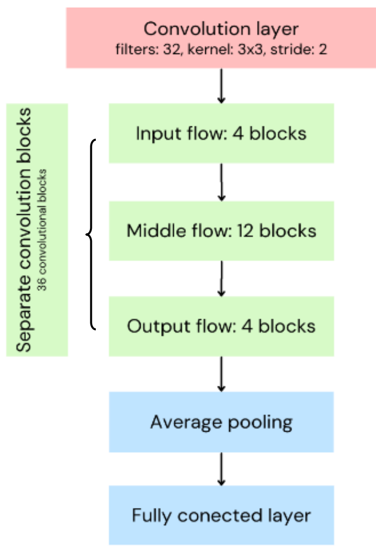

Fig. 4: Block diagram of NN Xception architecture.

Model training

Training a neural network is a crucial step in the machine learning process, affecting its ability to generalize and the accuracy of its predictions. To achieve the best results, it is essential to carefully optimize the hyperparameters. Choosing the right parameters is important for effective learning.

Several neural network models were trained to find the best model for automatic detection of intracapsular ruptures. Weights were set before comparing the models. The main performance indicator used to select the most relevant model was TPR and TNR on the test set, which best reflects the model's ability to generalize and successfully classify new, unseen images. Based on this criterion, the model with the best result was selected and is further described in the results chapter (Table 1). The augmentation was performed to increase the variability and robustness of the training. Augmentation techniques included random rotations and image shifts along the X and Y axes (Table 2).

Statistical Evaluation of the Model

The statistical evaluation of a neural network model is a crucial step in assessing the quality and reliability of the predictions generated by the model. The goal is to determine how accurately the model can predict based on training and validation data, and how well its predictions generalize to testing, i.e., unseen data.

In machine learning, a confusion matrix is used for statistical evaluation. Two classes are considered: Ruptures and Background (Fig. 5):

TP (True Positive)—positive pixels that have been classified as positive.
FP (False Positive)—pixels that are negative but have been classified as positive.
TN (True Negative)—negative pixels that have been classified as negative.
FN (False Negative)—pixels that are positive but have been classified as negative [11].

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		Predicted	
		Ruptures	Background
Actual	Ruptures	TP	FN
	Background	FP	TN

Fig. 5: Confusion matrix.

The value of true positive rate (TPR) indicates the classification model's ability to correctly identify positive pixels, such as in medical diagnostics, which detects the presence of a specific pathology.

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{1}$$

The value of true negative rate (TNR) represents the classification model's ability to correctly identify negative pixels, i.e., negative cases.

$$\mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{2}$$

Results

The training of the Xception neural network was performed on a GPU using the Adam optimization algorithm, which minimizes the model's loss function and thus achieves the highest possible TPR. The TNR value is comparable to ResNet-18. During training, the initial learning rate was set to 10^{-3}, ensuring fast convergence without skipping optimal solutions. The training was conducted for 50 epochs with a minibatch size of 32, meaning that at each learning step, small subsets of the training data (minibatches) were provided to the model, which improves learning stability and reduces the risk of overfitting.

The Xception network achieved the best results, primarily due to well-chosen hyperparameters (50 epochs, Adam, minibatch of 32). ResNet-18 had almost comparable results to Xception but with a simpler architecture and shorter training time. The ResNet-50 network showed lower performance compared to the previous models.

Several models were trained with different networks and different hyperparameter settings. The models were applied to testing, i.e., new data, from 5 patients (approximately 100 slices).

According to the TPR and TNR metric, the highest TPR (true positive rate) on the test data was achieved by model 38Xc (TPR = 0.954) which used the Xception neural network. The TNR (true negative rate) reaches the same value as the 2Xa model (Table 3). The results from the detection of model 38Xc can be seen in Fig. 6.

Table 3: Results of individual models.

	Metrics	Xception: Model 38Xc	ResNet-18: Model 2Xa	ResNet-50: Model5
Train	TPR	0.940	0.926	0.927
	TNR	0.997	0.982	0.980
Test	TPR	0.954	0.948	0.943
	TNR	0.867	0.869	0.683

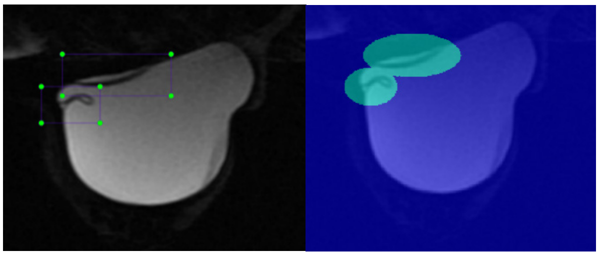

Fig. 6: Sample results from detection: Annotated image (left). Detected NN rupture (right).

Discussion

The work focuses on detecting intracapsular breast implant ruptures using pre-trained neural networks. The aim was to develop a semi-automatic method for detecting intracapsular ruptures of breast implants based on MRI image data. Three selected neural networks were used in this work. When comparing the three trained models, Xception, ResNet-18, and ResNet-50, it is evident that each model had its strengths and weaknesses depending on the hyperparameters used, input image size, and data augmentation settings.

The Xception network achieved the highest value TPR on the training, testing, and validation data. The TNR value is comparable to the Resnet-18 network. Although smaller than in other models, the image size of 299×299 is ideal for this architecture, designed to process smaller images efficiently. More extended training (50 epochs) and a larger minibatch (32) gave the network enough time and data to learn fine details. The Adam optimizer is known for its ability to quickly converge to a good solution, which was confirmed here. Thanks to more epochs and appropriate hyperparameters, the network was the most accurate in generalizing to new data (test set). Data augmentation, including image rotation and translation, provided the model with additional variations in the training data, increasing its ability to generalize. The smaller translation range (±10 pixels) minimized the risk of losing image details, allowing the network to better learn subtle features in the data. This mild augmentation was likely a critical factor in achieving high accuracy on the test data.

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In the case of the ResNet-18 network, the TPR (0.948) was slightly lower than that of the Xception network. The network is trained on larger images (500×500), which can be an advantage for capturing more extensive details but is also more computationally demanding. Using a smaller minibatch (16) and fewer epochs (15) may have resulted in the model needing more iterations to fully utilise its capabilities. The TPR value of the test data was very close to Xception but slightly lower. ResNet-18 is a simpler architecture than ResNet-50, making it a good compromise between accuracy and training speed. Data augmentation, including the image rotation and translation (shift), provided the model with additional variations in the training data, increasing its ability to generalize. The smaller translation range (-10 to 10 pixels) minimized the risk of losing image detail, allowing the network to better learn subtle features in the data. This mild augmentation was likely a critical factor in achieving high TPR and TNR on the test data.

ResNet-50 had the lowest values on the test data (TPR=0.93603, TNR=0.683), which may be related to the smaller number of epochs (10). The image size was again 500×500, which, along with the more extensive architecture (50 layers), places higher demands on training. The SGDM (Stochastic Gradient Descent with Momentum) optimizer is commonly used but may require more epochs than Adam (Adaptive Moment Estimation) to achieve better results. The lower number of epochs resulted in lower TPR and TNR, suggesting that ResNet-50 could benefit from longer training. However, this model may have greater potential if trained for longer, but this requires more computational power. As with ResNet-18, the data augmentation included rotations and large translation ranges (-50 to 50 pixels). Although this augmentation helped the model to better handle variations in the data, the larger translation range may have resulted in a loss of detail, which negatively affected the model's TPR and TNR on the test data.

In breast implant diagnostics, NN applications have already been used in US methods in the past. In their study, Salchenberger et al. [12] explored the potential of using NNs with radial basis functions for diagnosing breast implants based on ultrasound findings. The study included symptomatic and asymptomatic patients who underwent surgical removal of implants, followed by an analysis of ultrasound findings using NNs. The performance of these models was compared to radiologists' diagnostics using ROC curves.

The results indicate that NNs have the potential to improve the diagnosis of breast implant ruptures, especially in cases where rupture identification is challenging or ambiguous. The best results were achieved when neural network approaches were combined with physicians' diagnostics. The study suggests that NNs can serve as a valuable tool for medical decision-making and contribute to improved diagnostic accuracy [12, 13].

The TPR of model 38Xc (NN Xception) reached 95.4%, while the TNR was 86.7%. The TPR parameter is higher, indicating greater sensitivity than reported by Song in their meta-analysis, which focuses on the diagnostic accuracy of MRI for rupture detection. Whereas the TNR parameter is slightly higher within the analysed studies. The meta-analysis results indicate a TPR of 87% and a TNR of 89.8%. A combination of physician evaluation and a neural network could contribute to higher diagnostic accuracy [14].

Limitations

The main limitation of this work is the small amount of the data and the variability in the data. Moreover, the images were taken from two different types of MRI machines.

A small dataset can lead to overfitting the model, which learns details specific to the training data but needs to generalize better to new data. The variability of the data, meaning the different number of samples for each type of rupture, can also lead to data imbalance, which affects prediction TPR and TNR. However, if the data variability is well-represented, the model could gain the ability to recognize different types of ruptures and be helpful in a wide range of practical applications.

The different image resolutions from the two devices can cause problems during training if the data is not correctly normalized or adjusted. However, this variability can also be beneficial, as a model trained on different data types could be more flexible in practice and better applicable to various situations.

Conclusion

The aim of this paper was to develop an algorithm for semi-automatic detection of intracapsular rupture of breast implants based on MRI images. The rupture detection algorithm was designed and implemented using pre-trained neural networks in the Matlab environment. The proposed semi-automatic detection algorithm can be used as a decision support tool for rupture diagnosis or as a second opinion for radiologists. This approach could reduce the influence of subjective factors in diagnosis.

Xception proved to be the best model for this task. The model achieved the highest accuracy by combining smaller image sizes, longer training (50 epochs), the Adam optimizer and light enhancement (rotation and small translations).

ResNet-18 had similar results to Xception, but the smaller number of epochs and greater range of augmentation (larger translations) may have caused a slight loss of detail in the images, resulting in slightly lower true positive rate on the test data.

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ResNet-50 had the lowest true positive rate and true negative rate of the three models, probably due to the smaller number of epochs and the SGDM optimizer, which requires more iterations to achieve better results. The larger augmentation range may have caused additional complications when processing larger images.

All three models benefited from data augmentation, which increased their ability to generalize. Xception, with a softer augmentation setting, achieved the best balance between learning and generalization.

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