Title Of The Paper

Breast Lesion Classification in Ultrasound Images Using Deep Convolutional Neural Network.

Paper Link

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1. Summary

1.1. Hypothesis

This study explores the application of convolutional neural networks (CNNs) in the realm of medical image analysis, specifically focusing on the classification of breast lesions in ultrasound (US) images. Due to limited training data, a custom-built CNN with regularization techniques is employed, along with transfer learning from pre-trained models.

1.2. Contribution

The main objective of this paper is to evaluate the effectiveness of a straightforward CNN architecture for classifying images in an ultrasound image dataset by enhancing classifier performance through different optimization and regularization methods. It also involves assessing the custom-built network's performance via transfer learning compared to established architectures. Additionally, results will be compared with traditional machine learning methods using the same dataset to comprehensively evaluate the proposed CNN architecture's efficacy.

1.3. Methodology

This study presents a five-step method for tumor classification in ultrasound (US) images using Convolutional Neural Networks (CNNs). The approach involves preprocessing, automatic feature selection with CNN layers, logistic regression for image classification, hyperparameter tuning, and results evaluation. Techniques such as image resizing, database balancing, zero-centering, and normalization are applied. The CNN architecture features four convolutional layers, fully connected layers, and activation functions. Training parameters encompass weights initialization, various optimizers, stopping criteria, and batch size. Overfitting prevention includes image augmentation, L2 regularization, and dropout. The study assesses the proposed method against related work, compares the custom network with established CNNs through transfer learning, and contrasts results with radiologists' BI-RADS-based classifications. Performance metrics include accuracy, specificity, sensitivity, precision, false alarm, and Area Under the ROC curve (AUC). Comparisons with radiologists' findings based on BI-RADS categories are also introduced.

1.4.Conclusion

The proposed method achieves an initial accuracy of 85.98% and an AUC of 0.94, which significantly improves to 92.05% accuracy and 0.97 AUC after regularization. Comparative analyses with pre-trained CNN architectures and a state-of-the-art CAD system highlight the method's effectiveness. While surpassing a radiologist's analysis in terms of accuracy, precision, and specificity, the model falls short of matching the precision and specificity levels of one of the radiologists.

2.Limitations

2.1. First Limitation

One drawback of the proposed method is that, although it shows promise and overcomes traditional machine learning approaches, the study notes room for improvement due to the relatively small dataset. Convolutional Neural Networks (CNNs) tend to perform better with larger datasets, and the study suggests that a more extensive dataset could boost the model's effectiveness.

2.2. Second Limitation

Another limitation is that, although exceeding a radiologist in accuracy, the proposed method doesn't reach the precision and specificity levels of one radiologist. This highlights a limitation, indicating that while the model is accurate overall, it falls short in the delicate diagnostic precision and specificity shown by expert radiologists.

3. Synthesis

In future, the combination of three transfer learning architectures such as VGG, ResNet, and GoogLeNet can be integrated into a final classification layer to further improve the proposed system's performance. Moreover, the system can be used to detect tumors and cancer detection and evaluate how the use of the CNN model affects patients, including its impact on early detection rates, treatment decisions, and overall prognosis through research studies.