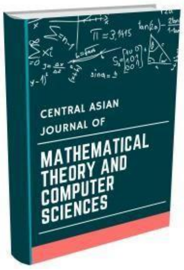
CENTRAL ASIAN JOURNAL OF MATHEMATICAL THEORY AND COMPUTER SCIENCES
https://cajmtcs.centralasianstudies.org/index.php/CAJMTCS
Volume: 06 Issue: 03 | July 2025 ISSN: 2660-5309

Article

Advanced Image Processing for Breast Cancer Detection Using CNN-Based Transfer Learning on Mammograms

Azhar Amer Alsoufi*[1]

1. Department of Electronic Technologies, Northern Technical University, Mosul, Iraq

* Correspondence: mti.lec250.azhar@ntu.edu.iq

Abstract: Breast cancer remains the most commonly diagnosed disease and the second leading cause of death among females. Statistically speaking, roughly one out of every eight American women was diagnosed with breast cancer last year. The precise identification of breast cancer also largely relies upon careful analysis of medical images. Though several Deep Learning (DL) algorithms have been employed to analyses such images, therefore, this study focuses on using a Convolutional Neural Network (CNN) to differentiate between different types of mammograms. The use of CNN in image recognition and visual processing has quickly drawn the attention of scholars. Therefore, in this current research, an approach is presented to extract patches from mammograms and utilize them to train the CNN, whereby the order of the section's feeds into the classification process. In addition, a transfer learning approach is utilized, in which a model created in the initial phase is later utilized as an initial model. Besides using single and multi-CNN and Artificial Neural Network (ANN) layers, two more approaches—Auto-Encoder and VGG16—are used to evaluate and compare the effectiveness of the models on different datasets.

Keywords: Breast Cancer, Convolutional Neural Network, Deep Learning, Artificial Neural Network, Auto-Encoder, VGG16

Citation: Alsoufi, A. A. Advanced Image Processing for Breast Cancer Detection Using CNN-Based Transfer Learning on Mammograms. Central Asian Journal of Mathematical Theory and Computer Sciences 2025, 6(3), 426-434.

Received: 8th Apr 2025
Revised: 11th Apr 2025
Accepted: 18th Apr 2025
Published: 28th Apr 2025

1. Introduction

This study provides crucial insights and statistics about breast cancer, underlining the rationale and objectives behind the current investigation. As one among the most common cancers globally, breast cancer remains a critical threat to women's wellbeing and ranks as the second primary cause of death in female-related illnesses. In 2019, roughly 1,762,450 fresh cases involving invasive breast cancer were recorded in the United States, with nearly 606,880 fatalities. The illness is generally recognized through unusual growth within breast tissue or the appearance of a lump either in the breast or underarm region. Identifying the illness during an early stage plays an essential role in decreasing mortality. Mammographic scans are commonly utilized for early breast cancer detection due to their affordability. These scans offer a preliminary means to gauge the likelihood of developing the illness. Although improvements in technology have enhanced cancer identification using mammograms, radiologists might still face obstacles in diagnosis because of the intricate structure of breast tissue. To assist radiologists, Computer-Aided Diagnosis (CAD) frameworks have been adopted. The traditional CAD method generally includes three critical phases: (a) detecting the tumor region in a mammogram, (b) retrieving features concerning the shape, texture, and density of the tumor, and (c) categorizing the tumor as either benign or malignant through those features. Though this strategy delivers acceptable levels of accuracy, there is potential for enhancement.

Recent breakthroughs in Deep Learning (DL) [1], [2], especially through Convolutional Neural Networks (CNNs), have shown notable outcomes in classifying medical scans, including mammograms. CNNs are likewise used efficiently across fields like image recognition, speech interpretation, and Natural Language Processing (NLP). A standard CNN contains a convolution layer, a pooling layer, and an activation layer. These elements extract significant, layered features from image content without manual involvement. In clinical scenarios, DL supports automated discovery of cancerous tissues. Training deep convolutional frameworks can prove difficult initially, largely since they depend on extensive amounts of data. Still, CNNs have shown remarkable precision in categorizing multiple medical image types. Given the persistent prevalence of breast cancer, early diagnosis stays essential to improving public health results. Estimates suggest that 42,260 patients (including 41,760 women and 500 men) may die due to breast cancer this year, with over 8% of women likely to receive the diagnosis throughout their lifetime.

Therefore, this study was created to enable quicker and more accurate diagnosis of breast cancer. Early discovery allows individuals to take prompt preventive decisions. Among current diagnostic options, mammography remains the most dependable tool for early diagnosis. Digital Mammography (DM), in particular, is recognized as the most precise approach. Nonetheless, research has shown that nearly 10–25% of tumors go undetected during scanning due to false-negative interpretations. To counter this limitation, the current investigation uses mammographic scans as data sources for training algorithms. Unlike former studies that depended on existing image banks, this effort incorporates a freshly compiled mammogram collection, aiming to improve prediction precision and reliability. The main purpose is to deploy prediction strategies that enhance both speed and detection precision. CNN is applied widely in the classification of medical imagery. Additionally, the study employs transfer learning, a DL approach growing in current research relevance. While CNN has been thoroughly studied in past works, this effort prioritizes reducing false-positive rates to strengthen diagnostic accuracy. The new dataset features actual mammograms acquired from hospitals treating patients diagnosed with breast cancer. This image set is intended to boost model effectiveness. Another major goal of this effort is making the detection platform available to users without technical expertise, including those from non-computer science backgrounds. Enabling public usage of such a system could deliver a valuable contribution to biomedical informatics. The detection mechanism involves five key steps i.e. image pre-processing, tumor detection, feature extraction, training dataset generation, and classifier training. Two commonly applied strategies for image classification in breast cancer screening are currently in practice.

Therefore, this study embraces the DL framework, with emphasis on CNN and transfer learning. For training and evaluation, two datasets are employed i.e. the Mammographic Image Analysis Society (MIAS) and the Digital Dataset for Screening Mammography (DDSM). The DDSM dataset holds 55,890 images, with around 14% labeled as positive cases and 89% as negative ones. Each image has dimensions of 299 × 299 pixels and undergoes pre-processing. The MIAS dataset includes 322 images, each with dimensions of 128 × 128 pixels. CNN has exhibited strong performance in fields such as image classification, object tracking, and image segmentation. This study strives to enhance breast cancer prediction via CNN by constructing a deep convolutional network architecture that labels mammograms as benign or malignant. To deal with limitations of dataset volume and training period, methods such as data augmentation and transfer learning are employed. The CNN network is initially trained on the MIAS collection and then evaluated on the CBIS-DDSM dataset using transfer learning, where one model trained on a particular dataset is used for another.

The study is as follows; in the next section, we will look at related works. Section III focuses on implementation. Section IV focuses on the experimental analysis. Section V discusses the study's shortcomings, and Section VI concludes with some conclusions and future work.

This section delivers a comprehensive overview of breast cancer detection, backed by earlier studies and established techniques in medical image classification. The primary emphasis is placed on exploring previous research that examined diverse techniques for classifying breast cancer via different types of images, including histopathological, 3D ultrasound, and mammographic images. Renowned datasets such as DDSM, MIAS, and BCRP have been commonly used in these analyses. However, in this study, the MIAS dataset, which includes mammographic images, has been chosen for testing. CNNs have been valuable in medical imaging tasks since the 1990s such as [3], [4], [5]. A major advantage of CNNs is their transferability, which allows the use of pre-trained models in healthcare environments. In the realm of transfer learning, two main strategies are identified: one extracts features from a pre-trained model to train a new classifier, while another replaces the fully connected layer of the network while keeping the rest of the structure. Numerous techniques have been introduced for feature extraction and classification using CNNs along with different types of classifiers such as [6], [7]. [8] have compared outcomes across classifiers and image formats. For instance, the IRMA dataset achieved 81.83% accuracy using discrete wavelet transform, and 83.74% with curvelet transform. Additional methods include such as [9], the application of genetic algorithms combined with C-means clustering, which have proven helpful in identifying affected regions. Furthermore, 3D breast ultrasound technology has been used effectively to separate fatty and non-fatty tissues. In [10], breast thermograms were used for identification by applying K-means clustering to highlight hot regions and apply color segmentation. In [11], Back Propagation Neural Networks (BPNN) were utilized as a microcalcification classifier, reaching a classification rate of 88.9% [12] used edge-based algorithms and threshold operators to extract tumor regions from ultrasound images, scoring an 89.2% classification rate based on the ROC curve.

Further [13] has applied logistic regression models to evaluate 32 image-based features for distinguishing benign and malignant tissues. These results support the efficiency of CNNs and transfer learning in processing large datasets for accurate detection outcomes. The aim of the suggested work is to classify benign and malignant breast cancer using CNNs along with transfer learning. Initially, the model was trained on a limited dataset, which was later scaled to larger datasets to enhance prediction accuracy. The model's performance was measured using metrics such as confusion matrix, sensitivity, specificity, and classification accuracy [14] applied CNN and USELM on 400 mammogram cases for breast mass detection and diagnosis. Their study reported an accuracy of 80.75%, sensitivity of 80.48%, with 82.43% accuracy for benign and 78.97% for malignant cases [15] used mammography images with Artificial Neural Networks (ANN) to detect breast tumors, resulting in improved accuracy, sensitivity, and positive predictive value [16] applied Region-based CNN (R-CNN) to datasets like DDSM-BCRP and INbreast , achieving a true positive rate of 0.86 at 1.2 false positives per image on INbreast, and 0.75 at 4.8 false positives per image on DDSM-BCRP [17] used a non-dominated sorting genetic algorithm to classify 949 mammograms, attaining 98.45% accuracy. This emphasizes the effectiveness of evolutionary algorithms in classification tasks [18] worked on histopathological images using CNN, achieving 99.28% accuracy, 98.65% sensitivity, and 99.57% specificity with the WDBC dataset, underlining the potential of CNNs in medical image classification.

2. Materials and Methods

To evaluate model performance, we experimented with different layers in both CNN and ANN, comparing results across multiple parameters. A CAD was also designed to predict whether a mammogram (x-ray) image is normal or cancerous, providing a binary outcome. Two datasets were employed for training and prediction: MIAS and CBIS-DDSM. MIAS contains 322 gray-scale mammogram images, all pre-processed and resized to 128 × 128. The images are divided equally between normal and cancerous cases. The CBIS-DDSM dataset, a curated and enhanced version of the DDSM, consists of 10,239 images in grayscale DICOM format. For this study, we used 1,400 mammogram images from CBIS-DDSM, categorized into normal, benign, and malignant classes. In terms of algorithms, the ANN used in our model is a multi-layer fully connected network comprising an input layer, multiple hidden layers, and an output layer. Each node in a layer is connected to every node in the next layer, allowing the network to go deeper by adding more hidden layers. The input layer in our ANN used 256 neurons with the Rectified Linear Unit (ReLU) activation function, while the output layer used two neurons to represent normal and cancerous classes, along with the softmax activation function. The softmax function computes the probabilities for each class and ensures that all output probabilities sum to 1. CNNs, designed specifically to process image inputs, were also utilized. CNNs can analyze and differentiate among high-dimensional images like 3D images. The structure of a CNN includes input and output layers, along with convolutional, pooling, and ReLU layers. The convolutional layer is the first step in feature extraction, preserving pixel relationships by learning features through small image regions using mathematical operations between an image matrix and a filter or kernel. For instance, a 5 × 5 image matrix convolved with a 3 × 3 filter produces a “feature map”. Pooling layers help reduce the number of parameters when processing large images. This process, known as spatial pooling or subsampling, reduces each feature map’s dimensionality while retaining essential information. There are various types of pooling such as max pooling, average pooling, and sum pooling. Max pooling selects the largest value from a filtered region. For instance, a 4 × 4 matrix input using a 2 × 2 filter with a stride of 2 would result in an output matrix containing the maximum value from each region covered by the filter.

In this study, we implemented multiple CNN layers, specifically four 2D convolutional layers and four 2D pooling layers, each using a 3 × 3 and 2 × 2 matrix respectively. Additionally, we applied three hidden layers using the ReLU activation function. Two fully connected layers followed, one with ReLU and the other with a softmax function for output prediction. VGG16, a notable CNN architecture known for its success in the 2014 ILSVR (ImageNet) competition, was also used. VGG16 is highly regarded for its consistent use of small 3 × 3 convolutional filters with stride 1 and same padding, followed by 2 × 2 max pooling layers with stride 2. This arrangement is repeated throughout the architecture. The network concludes with two fully connected layers and a softmax layer for classification. VGG16 comprises 16 weight layers and around 138 million parameters, making it one of the most powerful CNN architectures. To evaluate the performance of our CNN and ANN models in classifying benign and malignant cases, standard medical imaging evaluation metrics were used. These include Area Under Curve (AUC), Accuracy (ACC), Sensitivity (SEN), and Specificity (SPE). These metrics were calculated using a confusion matrix, which contains four outcomes: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

3. Results and Discussion

During the preprocessing process, raw mammogram inputs were filtered of distortions by employing an adaptive mean filter method. This method identifies distortions by computing average, variance, and relative relations, replacing affected pixels with averaged values. A CNN was implemented for feature representation, trained on mammographic inputs. The CNN network consisted of six layers—three convolutional blocks, two max-pooling processes, and one dense layer—taking image input sizes of 128 × 128. The accuracy of the model was calculated with the Receiver Operating Characteristic

(ROC) graph as shown in Figure 1, 2 and 3, indicating a true detection rate of 0.6 and a false alert rate of 0.3 to generate an AUC value of 0.57. The CNN approach yielded an estimated training precision of 94.8%, recall of 66.67%, and specificity close to 33%, as depicted in its evaluation and validation performance graphs. The loss in learning, meaning deviation in prediction, remained approximately 13%. A lower loss value means that the system gave more accurate predictions.

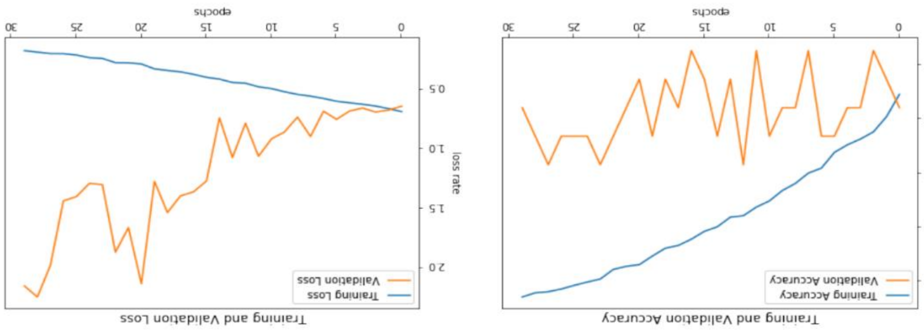

Figure 1. Training Accuracy and Training Loss with CNN (MIAS Dataset).

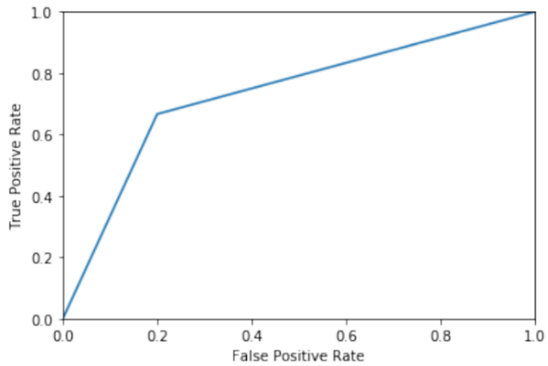

Figure 2. ROC Curve with CNN.

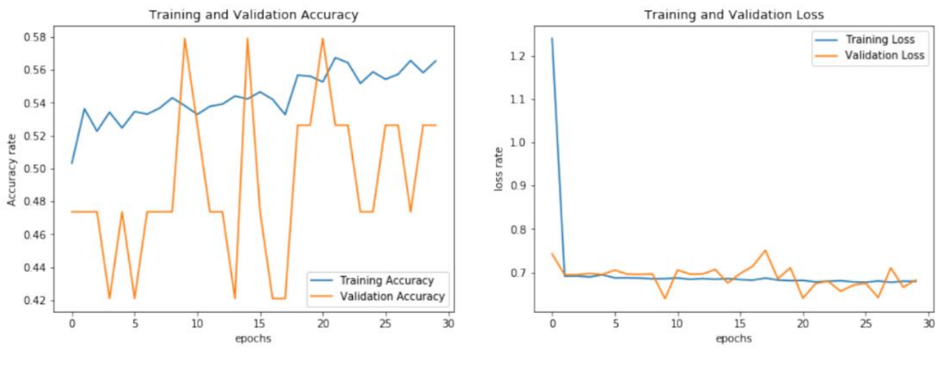

Figure 3. Training Accuracy and Training Loss using ANN (MIAS Dataset).

As indicated in Tables 1 and 2, the deep CNN network achieved 94.8% training accuracy with 13% learning loss, while a shallow ANN achieved 60.25% accuracy and 66.08% error. By comparison, the Autoencoder variant achieved 51.47% training outputs with 60% error rate, while a hybrid setup involving encoding plus sequencing achieved 60.25% accuracy and 22.26% loss measure. Validation statistics and error were computed using a different dataset to optimize architectures. When validation performance is higher than training accuracy, it usually indicates overfitting. The CNN method achieved 47.37% validation precision with 78% error, whereas the ANN achieved 71.43% precision with 64.10% loss. Using the CBIS-DDSM dataset, the CNN showed improved results, achieving 97.22% training score and an 8.56% learning loss. Validation reached 81.63% with 97.55% error, recall stood at 83.33%, specificity was 75%, and AUC ended at 0.53. Meanwhile, the ANN underperformed using identical data, delivering 55.25% training accuracy, 65.98% error, and 47.13% validation precision with 71.55% error. The Autoencoder scored 91.58% training precision and 69% during validation. Pre-trained VGG16 from Keras secured 72.7% training and 70.59% validation accuracy.

Table 1. A Summary Of Cnn and Ann-Based Methods using The Mias Dataset.

Metric	Multiple Layer of CNN	Single Hidden Layer of ANN	Auto Encoder	Encoding and Sequential Model Combination
Epochs	30	30	40	60
Training Accuracy	94.8%	60.25%	51.47%	60.25%
Training Loss	13%	66.08%	60%	22.26%
Validation Accuracy	47.37%	71.43%	71.43%	55.55%
Validation Loss	78%	64.10%	62.45%	24.85%
Sensitivity (Sn)	66.67%	66.67%	75%	66.67%
Specificity (Spc)	33%	33%	33%	47.72%
AUC	0.57	0.66	0.625	0.5
MCC	0.73	0.73	0.25	0.0
F1 Score	0.46	0.46	0.6	0.64

Table 2. A Summary of Cnn, Ann, Auto Encoder, Encoding, Sequential Model Combination, and The Vgg16 Approach Utilizing The Cbis-Ddsm Dataset.

Metric	Multiple Layer of CNN	Single Hidden Layer of ANN	Auto Encoder	Encoding and Sequential Model Combination	VGG16
Epochs	25	25	15	20	8
Training Accuracy	95.10%	58.40%	89.00%	65.25%	78.45%
Training Loss	10.15%	63.20%	28.50%	33.75%	41.60%
Validation Accuracy	79.80%	51.25%	66.80%	61.35%	73.20%
Validation Loss	22.90%	68.40%	17.45%	45.90%	36.85%
Sensitivity (Sn)	81.25%	54.30%	59.70%	63.15%	66.40%
Specificity (Spc)	69%	49%	52%	57%	60%
AUC	0.77	0.58	0.61	0.65	0.70
MCC	0.32	0.18	0.27	0.36	0.41
F1 Score	0.74	0.43	0.55	0.61	0.68

In comparing MIAS to CBIS-DDSM datasets, findings showed that CBIS-DDSM consistently provided better performance across methods. Specifically, CNN noted enhanced performance when used on CBIS-DDSM, reducing learning loss from 13% to 8.56%. Though with increased validation errors, increases in recall and specificity show improved performance. This finding highlights the manner in which model success relies greatly on dataset quality and content. CAD software now aids radiologists in assessing mammograms that tend to be difficult to read. Architectures like CNN and ANN are powerful classifiers for detecting aberrant growths, and their depth is helpful to comprehend detailed image information. In this task, both MIAS and CBIS-DDSM were used and CNN delivered best results utilizing CBIS-DDSM—yielding 97.22% training and 81.63% validation accuracy. The outcomes yielded from this study emphasize the essential contribution of architectural depth and data preprocessing towards enhancing accuracy in classification. As noted, deeper models like CNNs always perform better than shallower models when used with high-quality datasets like CBIS-DDSM. The performance of CNNs is due to their capacity to learn spatial hierarchies of features using layered filtering mechanisms. Their architecture facilitates automated feature extraction, eliminating the need for manual intervention and facilitating scalability across larger datasets. Moreover, the preprocessing phase also had a large impact on performance results. The adaptive mean filter contributed to enhancing input quality by reducing noise and distortions, which had direct effects on improved model generalization.

Limitations

In order to facilitate functionality, the system was designed such that each feature functioned correctly and contributed to the detection process. Reliability was achieved through creating a model that produced reliable and consistent outputs to enable users, particularly women, to make effective medical decisions. Usability was enhanced through an easy and simple interface, ensuring the application is easy to operate for individuals with minimal or no technical knowledge. Efficiency involved streamlining the software to perform efficiently using limited resources. Maintainability guaranteed that the tool would be readily modifiable when new data and medical technology become available. Portability permitted the software to run on many platforms, which made it versatile across various healthcare environments and readable to users not conversant with breast cancer. Some limitations were considered during development. One key technical challenge was the high cost of imaging modalities such as histopathological and 3D ultrasound images, which are costlier than mammography. To manage this, mammography images were selected as the primary dataset for model training and validation to make the solution more affordable. Ethical data collection hurdles also arose since hospitals were reluctant to release patient records due to confidentiality issues. This limited access to genuine datasets. Social factors created an additional layer of complexity because some women don't visit clinics out of shame or stigma, causing delay in diagnosis and adequate treatment. Hence, creating awareness for early detection remains crucial to enable timely medical care. The software was meant to be affordable and user-oriented, especially for areas where sophisticated diagnostic systems are not easily available. Focusing on simplicity and affordability, the tool is meant to enable early breast cancer diagnosis for underprivileged populations. The study showcases a comprehensive approach, combining ethical procedures, international software principles, and practical limits to come up with a reliable detection platform.

4. Conclusion

This study was centred on developing a CAD system for the identification and detection of benign and malignant breast cancer cases from digital mammograms. Spanning eight months, the study explored different feature extraction methods, different settings of neural networks, and different transfer learning methods. Of these, the application of modified features proved to be more efficient in discriminating between benign and malignant patterns. To construct the classification system, models were trained with CNN, ANN, and VGG16 architecture, all of which exhibited improvement in the accuracy of classification. Moreover, Autoencoder, which is a technique under transfer learning, was utilized to measure model performance. Experiments were conducted on the MIAS and CBIS-DDSM datasets, and results showed that multilayer CNNs always yielded the highest accuracy for both datasets. For performance analysis, important measures like sensitivity, specificity, AUC, and MCC were utilized to test the models. The current study included training and testing of different models to analyze their classification capabilities. In the future, the study will improve classification rates towards approaching near-perfection levels and create a more optimized CNN algorithm for better performance. The final goal is to be part of research that supports early detection and toward creating effective diagnostic tools that may save lives.

REFERENCES

[1] N. Marwah, V. K. Singh, G. S. Kashyap, and S. Wazir, “An analysis of the robustness of UAV agriculture field coverage using multi-agent reinforcement learning,” *International Journal of Information Technology*, vol. 15, no. 4, pp. 2317–2327, May 2023, doi: 10.1007/s41870-023-01264-0.

[2] G. S. Kashyap, K. Malik, S. Wazir, and R. Khan, “Using Machine Learning to Quantify the Multimedia Risk Due to Fuzzing,” *Multimedia Tools and Applications*, vol. 81, no. 25, pp. 36685–36698, Oct. 2022, doi: 10.1007/s11042-021-11558-9.

[3] R. Mishra, O. Daescu, P. Leavey, D. Rakheja, and A. Sengupta, “Convolutional neural network for histopathological analysis of osteosarcoma,” *Journal of Computational Biology*, Mary Ann Liebert, Inc., Mar. 2018, pp. 313–325, doi: 10.1089/cmb.2017.0153.

[4] G. Atteia *et al.*, “Adaptive Dynamic Dipper Throated Optimization for Feature Selection in Medical Data,” *Computers, Materials & Continua*, vol. 75, no. 1, pp. 1883–1900, Feb. 2023, doi: 10.32604/cmc.2023.031723.

[5] H. Muhammad *et al.*, “Unsupervised subtyping of cholangiocarcinoma using a deep clustering convolutional autoencoder,” in *Lecture Notes in Computer Science*, Springer, 2019, pp. 604–612, doi: 10.1007/978-3-030-32239-7_67.

[6] R. H. J. M. Kurvers *et al.*, “How to detect high-performing individuals and groups: Decision similarity predicts accuracy,” *Science Advances*, vol. 5, no. 11, Nov. 2019, doi: 10.1126/sciadv.aaw9011.

[7] M. T. Shaban, C. Baur, N. Navab, and S. Albarqouni, “Staingan: Stain style transfer for digital histological images,” in *Proceedings of the International Symposium on Biomedical Imaging*, IEEE, Apr. 2019, pp. 953–956, doi: 10.1109/ISBI.2019.8759152.

[8] J. G. Precious and S. Selvan, “Detection of Abnormalities in Ultrasound Images Using Texture and Shape Features,” in *Proceedings of the 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT)*, IEEE, Nov. 2018, doi: 10.1109/ICCTCT.2018.8551174.

[9] B. Chaix, G. Delamon, A. Guillemassé, B. Brouard, and J. E. Bibault, “Psychological distress during the COVID-19 pandemic in France: A national assessment of at-risk populations,” *General Psychiatry*, vol. 33, no. 6, p. 100349, Nov. 2020, doi: 10.1136/gpsych-2020-100349.

[10] R. H. J. M. Kurvers, S. M. Herzog, R. Hertwig, J. Krause, and M. Wolf, “Pooling decisions decreases variation in response bias and accuracy,” *iScience*, vol. 24, no. 7, p. 102740, 2021, doi: 10.1016/j.isci.2021.102740.

[11] K. Zormpas-Petridis *et al.*, “SuperHistopath: A Deep Learning Pipeline for Mapping Tumor Heterogeneity on Low-Resolution Whole-Slide Digital Histopathology Images,” *Frontiers in Oncology*, vol. 10, p. 3052, Jan. 2021, doi: 10.3389/fonc.2020.586292.

[12] J. Z. Cheng *et al.*, “Computer-Aided Diagnosis with Deep Learning Architecture: Applications to Breast Lesions in US Images and Pulmonary Nodules in CT Scans,” *Scientific Reports*, vol. 6, no. 1, pp. 1–13, Apr. 2016, doi: 10.1038/srep24454.

[13] N. Dong *et al.*, “Reinforced auto-zoom net: Towards accurate and fast breast cancer segmentation in whole-slide images,” in *Lecture Notes in Computer Science*, Springer, 2018, pp. 317–325, doi: 10.1007/978-3-030-00889-5_36.

[14] U. R. Acharya *et al.*, “A Novel Algorithm for Breast Lesion Detection Using Textons and Local Configuration Pattern Features with Ultrasound Imagery,” *IEEE Access*, vol. 7, pp. 22829–22842, 2019, doi: 10.1109/ACCESS.2019.2898121.

[15] K. D. Miller *et al*., "Cancer statistics for adolescents and young adults, 2020," *CA: A Cancer Journal for Clinicians*, vol. 70, no. 6, pp. 443–459, Nov. 2020, doi: 10.3322/caac.21637.
[16] D. Wang, A. Khosla, R. Gargeya, H. Irshad, and A. H. Beck, "Deep Learning for Identifying Metastatic Breast Cancer," Jun. 2016. [Online]. Available: https://arxiv.org/abs/1606.05718v1
[17] W. Yue, Z. Wang, H. Chen, A. Payne, and X. Liu, "Machine learning with applications in breast cancer diagnosis and prognosis," *Designs*, May 9, 2018, doi: 10.3390/designs2020013.
[18] I. Carmichael *et al*., "Joint and Individual Analysis of Breast Cancer Histologic Images and Genomic Covariates," *Annals of Applied Statistics*, vol. 15, no. 4, pp. 1697–1722, Dec. 2021, doi: 10.1214/20-AOAS1433.