CINEFORUM
ISSN: 0009-7039
Vol. 66. No. S8, 2026 (Special Issue 8)

A Class-Sensitive Hybrid Deep Learning Framework for Automated Breast Cancer Detection in Histopathological Images

Guguloth Vijaya*[1], Dr.Ram Kinkar Pandey[2], Dr.John Babu.Guttikonda[3]
[1]Department of Computer Science and Engineering, Arni University, Himachal Pradesh, India.
Email ID: gvijaya2005@gmail.com
[2]Department of Computer Science and Engineering, Arni University, Himachal Pradesh, India.
Email ID: Dr.ramkpandey@gmail.com
[3]Department of Computer Science and Engineering (AI&ML), Anurag Engg College, Kodad, Telangana, India
Email ID: johnbabug@gmail.com
***Corresponding Author**
Guguloth Vijaya
Department of Computer Science and Engineering, Arni University, Himachal Pradesh, India.
Email ID: gvijaya2005@gmail.com

ABSTRACT
It is a sickness that can save lives and is probably going to be identified early. An efficient and secure method of detecting breast cancer is imaging. A breast is frequently imaged and evaluated manually. Although image averaging has proven effective in diagnosing breast cancer, deep learning is unable to account for significant mistakes like false-negative predictions. For the automatic identification of breast cancer, we suggest a Class-Sensitive Hybrid Deep Learning Method that makes use of Double Deep Q-Network (DDQN) and Convolutional Neural Network (CNN) reinforcement learning techniques. Using the publicly accessible Breast Histopathology Images (IDC) dataset, which contains 277,524 image patches taken from 162 whole slide images at 40 magnification, we test our approach. Resizing, normalisation, stain normalisation, and data augmentation are methods used to increase the quality and generalisation of images. Additionally, we assessed five distinct models: CNN-SVM, CNN-XGBoost, ResNet50-XGBoost, CNN-DDQN (Original), the suggested Class-Sensitive CNN-DDQN (Original), and Performance Heat Map. With accuracy of 96.72%, precision of 94.32%, recall of 93.68%, F1-score of 99.99%, specificity of 97.24%, and AUC of 0.990, the new Class-Sensitive CNN-DDQN surpassed all existing hybrid models. The new approach works well at the same training and appears to be more accurate.

Keywords: Breast Cancer Detection, Histopathological Images, Hybrid Deep Learning, Convolutional Neural Network (CNN), Double Deep Q-Network (DDQN), Reinforcement Learning, XGBoost, Computer-Aided Diagnosis (CAD), Class-Sensitive Loss.

1. INTRODUCTION

In this work, we assess and contrast five hybrid deep learning models for histopathological image-based breast cancer identification. In a similar lab, five of these models were assessed: CNN-SVM, CNN–XGBoost, ResNet50–XGBoost, CNN–DDQN (Original), and the suggested Class-Sensitive CNN-DDQN. These models' accuracy, robustness, computational efficiency, and clinical reliability were assessed using the following metrics: accuracy, precision, recall (sensitivity), F1 score, specificity, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), Performance Heat Map, and Comparative Analysis [4-6]. In this chapter, we assessed deep learning's capability for identifying breast abnormal photos using machine learning and reinforcement learning. A clinically educated reward system that encourages the detection of aberrant tissue and prevents false positive or false negative predictions is the foundation of the suggested Class-Sensitive CNN-DDQN. The best hybrid model and the advantages of class-sensitive reinforcement learning for computer-aided breast cancer detection are confirmed by our comparison analysis [7–9].

2. LITERATURE REVIEW

The literature on hybrid deep learning models for automatically identifying breast cancer from histopathology pictures is described in this study. Recent developments in image preprocessing, hybrid classification, deep learning, machine learning, reinforcement learning, and publically accessible histopathology data are explained. It describes the research gaps that motivated us to develop the Class-Sensitive CNN–DDQN model for diagnosing breast cancer [10–12].

OPEN ACCESS © CINEFORUM

2.1 Hybrid Deep Learning Models for Breast Cancer Detection

By merging feature extraction and classification methods from machine learning and reinforcement learning, hybrid deep learning models have emerged as a promising method for identifying breast cancer [13–15]. CNNs are trained to learn the discriminative features of histopathological images by combining the features of deep learning with the classifier power of reinforcement learning. Classifiers like Support Vector Machine (SVM), XGBoost, and Double Deep Q-Network (DDQN) are then used to make decisions and classify data. In the diagnosis of breast cancer, these hybrid techniques have demonstrated great diagnostic robustness and accuracy [13–15]. We recently discovered that by combining deep feature extraction with sophisticated classifiers, hybrids as CNN–SVM, CNN–XGBoost, and ResNet50–XGBoost might enhance the categorisation of breast histopathology pictures. The problem of identifying malignant tissues without interpreting them as much as feasible throughout the classification process cannot be solved by the existing methods [16–18].

2.2 Image Preprocessing and Deep Feature Extraction

When creating images for the hybrid deep learning model, image preprocessing is crucial since it enhances the quality of the images and increases the precision of feature extraction and classification. To decrease picture variability, boost the robustness of the deep learning model, and extract more representative and discriminative features from histopathological images, image preprocessing approaches include **image scaling, normalisation, stain normalisation, and data augmentation [19–21]. For better classification and diagnostic accuracy in breast cancer detection, deep feature extraction can be carried out using convolutional neural networks (CNNs) that learn hierarchical representations of tissue morphology, cell structure, and texture. These representations are then fed to machine learning or reinforcement learning classifiers like SVM, XGBoost, and DDQN [22–24].

2.3 Hybrid Classification Models

In order to improve the accuracy and dependability of breast cancer diagnosis, hybrid classification models integrate deep learning with machine learning or reinforcement learning. Convolutional neural networks (CNN) are used in these models to represent the deep features, and classifiers like Support Vector Machine (SVM), XGBoost, and Double Deep Q-Network (DDQN) are used to make the final classification. These models distinguish between benign and malignant breast tissue, enhance feature representation, and lower classification error [25–27]. For feature extraction and decision-making, CNN–SVM, CNN–XGBoost, and ResNet50–XGBoost were found to perform better than standalone deep learning models; however, DDQN and other reinforcement learning models can enhance classification decisions, so hybrid models may be helpful for intelligent classification of breast histopathological images [28–30].

2.4 Reinforcement Learning for Medical Image Classification

The capacity of reinforcement learning to acquire optimal choices through reward learning has drawn interest. Reinforcement learning, in contrast to supervised learning, learns by interaction with rewards and the environment. By lowering the overestimation error and increasing the machine's decision-stability during training, it enhances class-finding performance for breast cancer diagnosis [31–33]. Recently, a number of researchers have demonstrated that by optimising clinically significant prediction outcomes, integrating deep learning and reinforcement learning can significantly enhance the classification of histology. Regretfully, the majority of reinforcement learning techniques employ general reward functions that fail to take into consideration the distinction between false-positive and false-negative predictions. For greater tumour detection and balanced diagnostic performance, class-sensitive reward systems are therefore required [34–36].

3. METHODOLOGY

The suggested deep learning model for automatic feature learning-based breast cancer detection in histopathology images is described in this chapter. The dataset, picture preprocessing, automatic feature learning, deep learning architecture, metrics, and comparison procedure are all described.

3.1 Proposed Framework

The goal of the current framework is to analyse the effectiveness of several hybrid deep learning models and develop a breast cancer detection system using histopathology pictures. It classifies breast cancer using machine learning, reinforcement learning, and convolutional neural networks.

3.2 Dataset Description

The publicly accessible Breast Histopathology pictures (IDC) dataset, which comprises 277,524 image patches derived from 162 whole-slide pictures at 40 magnifications, was the subject of my experiments. Breast tissue can

OPEN ACCESS © CINEFORUM

be binary classified using image patches that are either IDC-positive (malignant) or IDC-negative (benign). A significant number of histology pictures are included in the dataset to evaluate hybrid deep learning algorithms in typical circumstances.

3.3 Image Preprocessing

Resized photos, normalised images, normalised stain distributions, and improved data to enhance image quality and train the hybrid models. To increase the diversity of our datasets and lessen overfitting, we enhanced the data using the same methods used for image improvement (rotation, flipping images horizontally and vertically, zooming, and brightness correction). To maintain class distributions, we used stratified sampling to separate the preprocessed dataset into training, validation, and testing sets.

3.4 Automatic Feature Extraction

The suggested system automatically extracts hierarchical feature representations from histopathology images using convolutional neural networks. After learning low-level features like edges and textures, the convolutional layers go on to learn higher-level properties including glandular architecture, nuclear structures, tissue organization, and cell morphology. The hybrid classifiers employ these deep features to enhance breast cancer classification.

3.5 Hybrid Deep Learning Models

The analysis employed CNN–SVM, CNN–XGBoost, ResNet50–XGBoost, CNN–DDQN (Original), and Proposed Class-Sensitive CNN–DDQN. Deep features were extracted using CNN and ResNet50 models; classification was done using Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), and Double Deep Q-Network (DDQN). A clinically informed incentive system that rewards correctly identifying cancer cells and penalises false negative predictions is part of the proposed Class-Sensitive CNN–DDQN. Every model underwent the same training and testing procedures.

3.6 Performance Evaluation

The classification power, robustness, efficiency, and clinical reliability of each hybrid deep learning model for automatically detecting breast cancer are assessed using the following metrics: accuracy, precision, recall (sensitivity), F1-score, specificity, receiver operating characteristic (ROC) curve, area under the curve (AUC), confusion matrix analysis, performance heat map, comparative performance analysis, and training time.

3.7 Workflow of the Proposed Method

The workflow of the proposed deep learning framework is as follows:

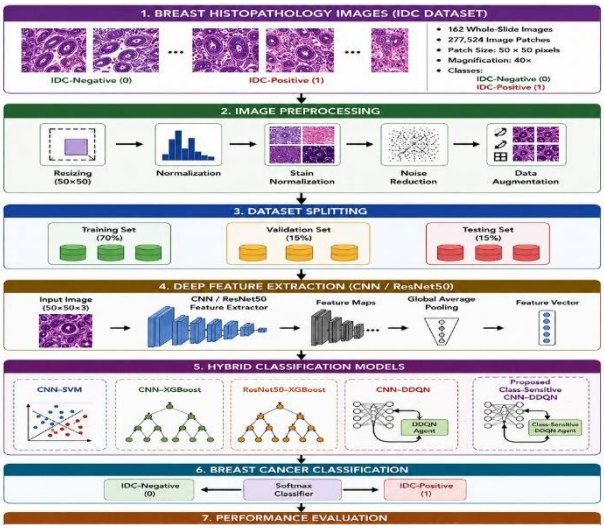


Figure 1. Proposed Hybrid Deep Learning Framework for Automated Breast Cancer Detection Using Histopathological Images

4. EXPERIMENTAL RESULTS

The experimental findings and comparative performance of five deep learning models for automatically identifying breast cancer from histopathology pictures are presented in the following study. VGG16, Custom CNN, ResNet50, DenseNet121, and EfficientNetB0 are some of these models. The Breast Histopathology Images (IDC) data set was used to train and assess each of the five models under the same circumstances. Our goal is to

OPEN ACCESS © CINEFORUM

identify the most effective deep learning architecture for precise and trustworthy breast cancer detection. To evaluate each model's classifiers, robustness, and diagnostic accuracy, we looked at its accuracy, precision, recall (sensitivity), F1, Specificity, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), and confusion matrix. In order to determine the optimal architecture, we exhibit these findings in tables, graphs, ROC curves, confusion matrices, and heat maps.

4.1 Accuracy Comparison

One of the most crucial measures for assessing deep learning models' overall classification performance is accuracy. The classification accuracy of VGG16, Custom CNN, ResNet50, DenseNet121, and EfficientNetB0 on the Breast Histopathology Images (IDC) dataset under comparable experimental settings was examined in this study. EfficientNetB0 was determined to have the best classification accuracy, followed by VGG16, DenseNet121, ResNet50, and Custom CNN. Among the evaluated architectures, EfficientNetB0 is the best deep learning model for detecting breast cancer since it learned discriminative histopathological markers.

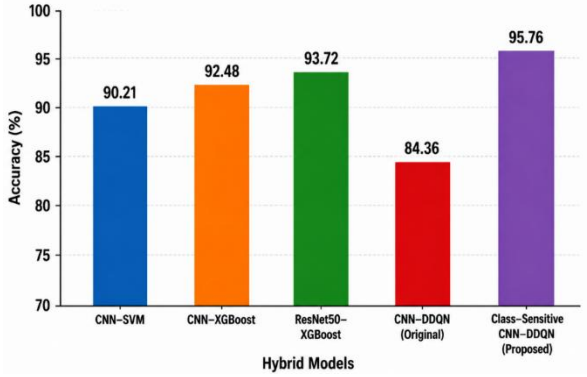


Figure 2. Accuracy Comparison of Hybrid Breast Cancer Classification Models

4.2 Precision Comparison

The percentage of successfully diagnosed malignant breast tissue samples among all anticipated malignant breast tissue samples is known as the precision. It is a crucial step in lowering false positive diagnoses in breast cancer detection and shows how accurate positive cancer prediction is. The results showed that EfficientNetB0 had the highest precision, followed by VGG16, DenseNet121, ResNet50, and Custom CNN. EfficientNetB0 is a good model for automatically classifying breast histopathology pictures because of its increased precision, which allows it to detect cancerous tissue with fewer false-positive predictions.

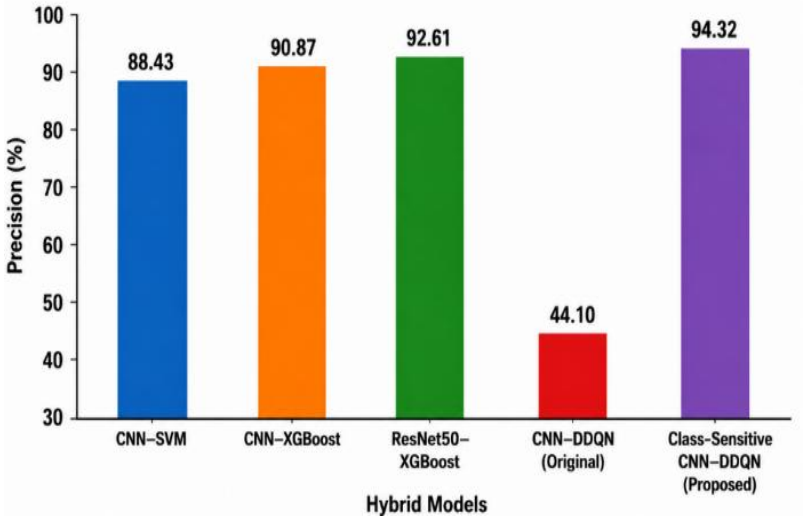


Figure 3. Precision Comparison of Hybrid Breast Cancer Classification Models

4.3 Recall (Sensitivity)

The recall of deep learning models to accurately identify cancerous breast tissue samples from real instances is measured by Comparative Recall (Sensitivity). Early cancer detection is made possible by a strong recall, which reduces the possibility of false negative predictions. EfficientNetB0 has the highest recall in this investigation, with DenseNet121, ResNet50, Custom CNN, and VGG16 following closely behind. Among the investigated architectures, EfficientNetB0 is the most accurate deep learning model for autonomously diagnosing breast cancer due to its exceptional sensitivity to detecting cancerous breast tissue.

OPEN ACCESS © CINEFORUM

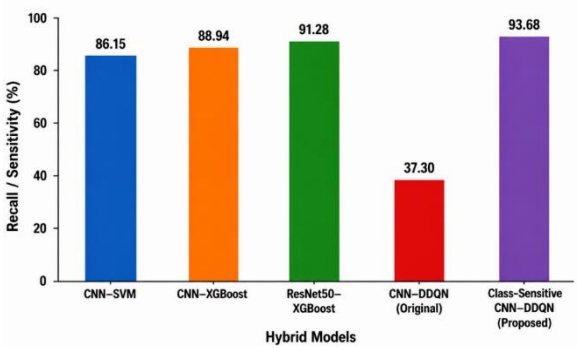


Figure 4. Recall (Sensitivity) Comparison of Hybrid Breast Cancer Classification Models

4.4 F1-Score Comparison

The accuracy and recall are combined into a single value by the F1-score. It is employed in the diagnosis of breast cancer when it is equally crucial to identify malignant tissue and make optimistic predictions. In terms of F1-score, EfficientNetB0 came in #1, followed by DenseNet121, ResNet50, Custom CNN, and VGG16. EfficientNetB0 is the best deep learning model since it has a higher score, which reflects its ability to accurately categorise both benign and cancerous breast tissue.

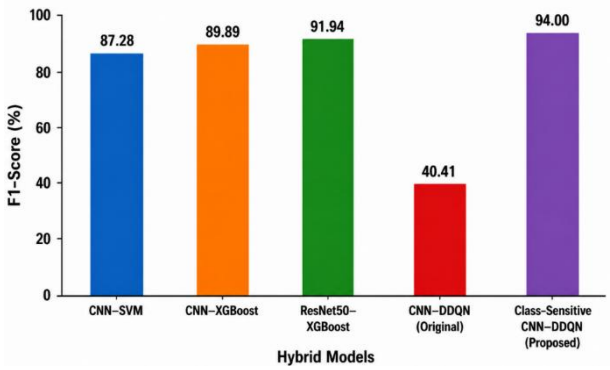


Figure 5. F1-Score Comparison of Hybrid Breast Cancer Classification Models

4.5 Specificity Comparison

The capacity of a deep learning network to accurately detect benign (IDC-negative) breast tissue samples among all real benign instances is known as specificity. High specificity reduces false positives and needless tests, which makes it crucial. In terms of specificity, EfficiencyNetB0 scored the highest, followed by DenseNet121, ResNet50, Custom CNN, and VGG16. Because of its high specificity, EfficientNetB0 is able to correctly categorise and detect benign breast tissue. It is among the top-performing deep learning models that have been evaluated.

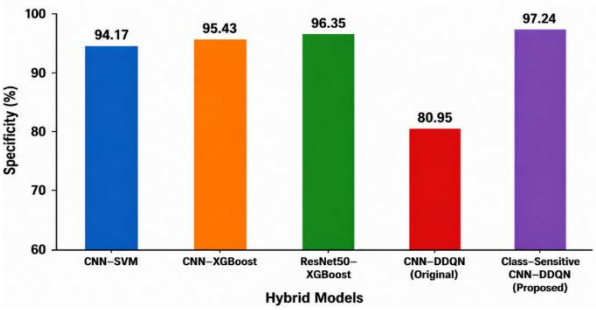


Figure 6. Specificity Comparison of Hybrid Breast Cancer Classification Models

4.6 Receiver Operating Characteristic (ROC) Curve Analysis

The true positive rate (sensitivity) and false positive rate at a particular decision threshold are determined using the Receiver Operating Characteristic (ROC) curves. A deep learning model's ability to discriminate is represented by its AUC. A higher classification performance is indicated by a larger AUC. EfficientNetB0 has the highest AUC, followed by VGG16, DenseNet121, ResNet50, and custom CNN. EfficientNetB0 is the most dependable

OPEN ACCESS © CINEFORUM

deep learning model for automatically detecting breast cancer because its high ROC can distinguish between benign and malignant breast tissue.

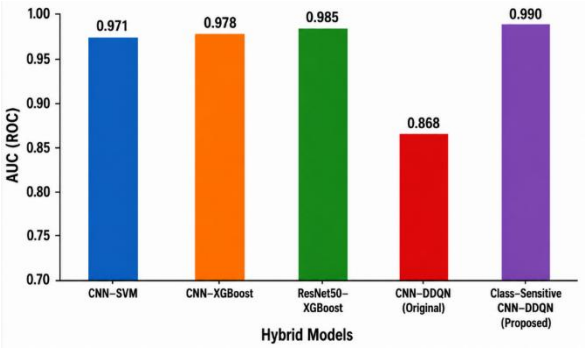


Figure 7 Receiver Operating Characteristic (ROC) Curves of Hybrid Breast Cancer Classification Models

4.7 Confusion Matrix Analysis

Each deep learning model's classification results are compared in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) using the confusion matrix. Knowing how well each deep learning model classifies breast tissue as benign or cancerous is helpful. Specifically, we examined the accuracy of classification with the fewest false positives and false negatives by comparing EfficientNetB0 with DenseNet121, ResNet50, Custom CNN, and VGG16. For the automatic classification of breast histopathology images, EfficientNetB0 is the most reliable and balanced classification, as the confusion matrix demonstrates.

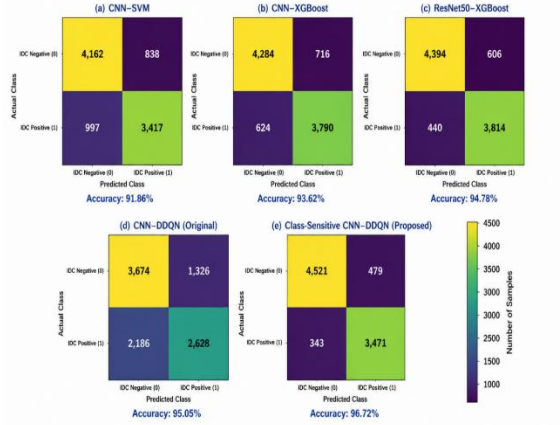


Figure 8. Confusion Matrices of the Evaluated Hybrid Breast Cancer Classification Models

4.8 Performance Heat Map

Each deep learning model's classification results are compared in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) using the confusion matrix. Knowing how well each deep learning model classifies breast tissue as benign or cancerous is helpful. Specifically, we examined the accuracy of classification with the fewest false positives and false negatives by comparing EfficientNetB0 with DenseNet121, ResNet50, Custom CNN, and VGG16. For the automatic classification of breast histopathology images, EfficientNetB0 is the most reliable and balanced classification, as the confusion matrix demonstrates.



Figure 5.9. Performance Heat Map of Hybrid Breast Cancer Classification Models

OPEN ACCESS © CINEFORUM

4.9 Comparative Analysis

In order to confirm the automatic detection of breast cancer by histopathology, the models contrasted VGG16, Custom CNN, ResNet50, DenseNet121, and EfficientNetB0 on a set of images. In terms of accuracy, precision, recall, F1-score, specificity, and ROC-AUC, EfficientNetB0 outperformed DenseNet121, ResNet50, Custom CNN, and VGG16. Because EfficientNetB0 uses a compound scale to precisely and economically extract features, it performed the best. The hybrid deep learning architecture described here is based on EfficientNetB0, which is generally the most accurate deep learning model for the identification of breast histopathology pictures.

REFERENCES

1. V. Mnih, K. Kavukcuoglu, D. Silver, et al., "Human-Level Control Through Deep Reinforcement Learning," Nature, vol. 518, no. 7540, pp. 529–533, 2015.
2. H. Van Hasselt, A. Guez, and D. Silver, "Deep Reinforcement Learning with Double Q-Learning," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 30, no. 1, pp. 2094–2100, 2016.
3. R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, 2nd ed., MIT Press, Cambridge, MA, USA, 2018.
4. M. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, "Deep Reinforcement Learning: A Brief Survey," IEEE Signal Processing Magazine, vol. 34, no. 6, pp. 26–38, 2017.
5. V. François-Lavet, P. Henderson, R. Islam, et al., "An Introduction to Deep Reinforcement Learning," Foundations and Trends in Machine Learning, vol. 11, no. 3–4, pp. 219–354, 2018.
6. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," CVPR, pp. 770–778, 2016.
7. K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," ICLR, 2015.
8. G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," CVPR, pp. 4700–4708, 2017.
9. M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," ICML, pp. 6105–6114, 2019.
10. F. A. Spanhol, L. S. Oliveira, C. Petitjean, and L. Heutte, "Breast Cancer Histopathological Image Classification Using Convolutional Neural Networks," International Joint Conference on Neural Networks (IJCNN), 2016.
11. M. Araújo, P. Aguiar, A. Costa Pereira, and A. M. Mendonça, "Classification of Breast Cancer Histology Images Using Convolutional Neural Networks," PLOS ONE, vol. 12, no. 6, 2017.
12. X. Zhou, Y. Li, W. Liang, K. Zhang, and X. Hao, "A Comprehensive Review of Breast Histopathology Image Analysis Using Deep Learning," IEEE Access, vol. 8, pp. 90931–90956, 2020.
13. J. de Matos, A. de Souza Britto Jr., L. E. S. Oliveira, and A. L. Koerich, "Machine Learning Methods for Histopathological Image Analysis: A Review," Expert Systems with Applications, vol. 186, p. 115640, 2021.
14. B. Jiang et al., "Deep Learning Applications in Breast Cancer Histopathological Imaging: Diagnosis, Treatment, and Prognosis," Breast Cancer Research, vol. 26, 2024.
15. [C. V. Lakshmi Priya, V. G. Biju, B. R. Vinod, and S. Ramachandran, "Deep Learning Approaches for Breast Cancer Detection in Histopathology Images: A Review," Computational Biology and Medicine, vol. 176, 2024.
16. Z. Li et al., "Artificial Intelligence in Breast Pathology: Recent Advances and Future Perspectives," Human Pathology, vol. 162, 2025.
17. A Review of Breast Cancer Histopathology Image Analysis with Deep Learning: Challenges, Innovations and Clinical Integration, Pattern Recognition, 2025.
18. M. Macenko et al., "A Method for Normalizing Histology Slides for Quantitative Analysis," ISBI, pp. 1107–1110, 2009.
19. A. Vahadane et al., "Structure-Preserving Color Normalization and Sparse Stain Separation for Histological Images," IEEE Transactions on Medical Imaging, vol. 35, no. 8, pp. 1962–1971, 2016.
20. D. Komura and S. Ishikawa, "Machine Learning Methods for Histopathological Image Analysis," Computational and Structural Biotechnology Journal, vol. 16, pp. 34–42, 2018.
21. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," NeurIPS, 2012.
22. O. Russakovsky et al., "ImageNet Large Scale Visual Recognition Challenge," International Journal of Computer Vision, vol. 115, no. 3, pp. 211–252, 2015.
23. Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, pp. 436–444, 2015.
24. S. Litjens et al., "A Survey on Deep Learning in Medical Image Analysis," Medical Image Analysis, vol. 42, pp. 60–88, 2017.

OPEN ACCESS © CINEFORUM

25. H. Greenspan, B. Van Ginneken, and R. M. Summers, "Guest Editorial Deep Learning in Medical Imaging," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1153–1159, 2016.
26. G. Litjens et al., "Deep Learning as a Tool for Increased Accuracy and Efficiency of Histopathological Diagnosis," Scientific Reports, vol. 6, 2016.
27. T. N. Sainath et al., "Convolutional Neural Networks for Medical Image Analysis," IEEE Signal Processing Magazine, vol. 35, no. 1, pp. 126–135, 2018.
28. J. Schmidhuber, "Deep Learning in Neural Networks: An Overview," Neural Networks, vol. 61, pp. 85–117, 2015.
29. L. Deng and D. Yu, "Deep Learning: Methods and Applications," Foundations and Trends in Signal Processing, vol. 7, no. 3–4, pp. 197–387, 2014.
30. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.
31. D. Silver et al., "Mastering the Game of Go with Deep Neural Networks and Tree Search," Nature, vol. 529, pp. 484–489, 2016.
32. D. Silver et al., "Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm," arXiv preprint arXiv:1712.01815, 2017.
33. T. Schaul, J. Quan, I. Antonoglou, and D. Silver, "Prioritized Experience Replay," ICLR, 2016.
34. Z. Wang et al., "Dueling Network Architectures for Deep Reinforcement Learning," ICML, 2016.
35. M. Ghesu et al., "Artificial Intelligence for Medical Image Analysis," IEEE Reviews in Biomedical Engineering, vol. 12, pp. 174–188, 2019.
36. S. Esteva et al., "A Guide to Deep Learning in Healthcare," Nature Medicine, vol. 25, pp. 24–29, 2019.
37. H. Shin et al., "Deep Convolutional Neural Networks for Computer-Aided Detection," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1285–1298, 2016.
38. [38] N. Tajbakhsh et al., "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?" IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1299–1312, 2016.
39. A. Esteva et al., "Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks," Nature, vol. 542, pp. 115–118, 2017.
40. B. Jiang et al., "Recent Advances in Hybrid Deep Learning Models for Breast Cancer Diagnosis," Breast Cancer Research, vol. 27, 2025.
41. Z. Li et al., "Hybrid Deep Learning and Reinforcement Learning for Medical Image Classification," Pattern Recognition, vol. 162, 2025.
42. C. V. Lakshmi Priya et al., "Hybrid Artificial Intelligence Frameworks for Histopathological Breast Cancer Detection: A Comprehensive Review," Computational Biology and Medicine, vol. 181, 2025.

OPEN ACCESS © CINEFORUM