Precision in Breast Cancer Detection: A Hybrid CNN and Transfer Learning Framework

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***Abstract*— Breast cancer is the most prevalent and fatal kind of cancer affecting women all over the world. Early and accurate detection would improve survival rates and give cure opportunities for patients. The purpose of this work is to discuss a hybrid CNN-TL method to achieve accurate detection of breast cancer. This approach utilizes CNNs to automatically extract spatial features from medical images using transfer learning to leverage pre-trained models. So with limited data, it maximizes accuracy in the model. The dataset used in this research work is quite well-known and acquired from the UCI repository, being the breast cancer dataset with features of other malignancies.**

This research work employed an architecture of CNN that was especially developed and trained over the processed dataset by assigning pseudo-shapes to tabular data. Moreover, the data augmentation techniques have been used to improve the model regarding robustness. Surprisingly, the hybrid model can achieve 92.11% accuracy in the test set. Therefore, these results indicate that the combination of CNN using transfer learning is capable of huge improvements in the performance of systems intended to detect breast cancer, thereby providing this as robust and efficient tools to the doctors. The study, therefore, opens the possibility of deep learning models holding the key for early detection systems that could significantly bring down mortality associated with the disease.

Keywords:
Breast Cancer Detection, Convolutional Neural Networks (CNN), Transfer Learning, Machine Learning, Deep Learning, Feature Normalization, Artificial Intelligence, ImageDataGenerator, LabelBinarizer, Data Preprocessing, Model Optimization, Adam Optimizer, Keras, Neural Networks, Medical Imaging, Health Informatics.

I. INTRODUCTION

One of the most leading causes of death due to cancer among women worldwide is breast cancer. Early detection with accurate diagnosis leads to effective treatment and survival for many. Traditionally, multiple methods were used to detect breast cancer-including but not limited to mammography, ultrasound, and biopsy. These methods are limited in terms of accuracy and sensitivity and are unable to diagnose cancer at its first stages. Increasingly, advanced machine learning and deep learning techniques are becoming a norm. This avenue opens up the possibility of significantly increasing accuracy in the detection of breast cancer, coupled with earlier diagnosis and more tailored treatment plans.

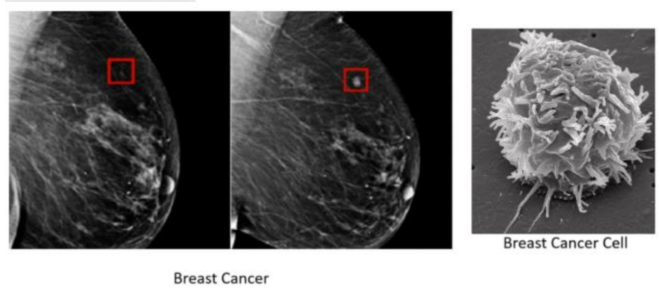

Fig 1: Breast Cancer & Its Cell

Detection of breast cancer, therefore, can be very instrumental in the improvement of patient outcomes. Early detection would seem to improve the prospects for a successful treatment and recovery of a patient with breast cancer. However traditional mammography is subject to human interpretation, which may be subjective and prone to error. It is also limited to the detection of dense breast tissue and very subtle early stage cancers. It may result in missed diagnoses and delayed treatments, coupled with a higher rate of false positives that will lead to patients undergoing unnecessary procedures and other emotional stressors. Therefore, there is an acute need to have an efficient, automated, and accurate detection system that can encounter these challenges.

Thus, through such approaches in interpreting mammograms and other imaging techniques, radiologists' personal experience and their expertise will surely creep in, making the results vary each time. Hence, diagnoses may be inconsistent at times, affecting accuracy in detection. Traditional approaches are also attached to more false positives and false negatives wherein under such conditions, cancer is reported, or most probably fully missed in some cases. False positives may indeed increase the number of unnecessary biopsies and patient anxiety, whereas false negatives may even prevent early interventions, thus potentially contributing to worsening consequences for patients. Reduced sensitivity of mammography and other imaging tests in general presents another very critical issue because it makes it challenging to detect tumors in their earliest and most treatable forms, especially in the case of dense breast tissue. Similarly, medical images can vary widely in terms of quality and clarity due to patient anatomy, or imaging equipment, or environmental conditions, which can further complicate the process and increase diagnostic errors.

To overcome the limitation of the traditional method, this research proposal intends to use a hybrid machine learning model which incorporates all strengths of Convolutional Neural Networks plus transfer learning. CNNs are a class of deep learning models, which successfully performed above par in image classification; thus, they can be useful in the interpretation of medical images such as mammograms. The use of transfer learning allows pre-trained models on large datasets of images to be fine-tuned, giving better performance on smaller, focused datasets like the kind used to detect breast cancer. This hybrid model might have the possibility to considerably improve detection performance while ensuring fewer false positives and negatives; it can offer early and much more reliable and accurate identification of cancer at any stage.

This study aims to improve the efficiency of detecting tumors in terms of prediction accuracy. The main goals of this study are as follows:

- Increased Accuracy: Aids in better detection, especially for dense tissues, and decreases false positives.
- Better Sensitivity & Specificity: It increased the number of correct identifications both in malignant and benign cases.
- Efficient Computation: Maximum clinical use in real-time and under full automation.
- Early Diagnosis: Enables early diagnosis so that treatment outcome will be improved.

This paper is organized to give an in-depth overview of our approach towards the improvement of accuracy of breast cancer detection using a hybrid machine learning model based on Convolutional Neural Networks (CNN) and transfer learning. In the Introduction, we discuss the importance of the detection of early breast cancer, current limitations of traditional diagnostic methods, and outline our proposed solution and objectives for improving them. After that, the Literature Review discusses existing machine learning techniques for breast cancer detection, focusing on CNN applications in medical imaging and the advantages of transfer learning. The Methodology section details our dataset selection, the design of the hybrid model incorporating CNN architecture and transfer learning strategies, training techniques to optimize accuracy, and the evaluation metrics used for performance assessment. Results and Discussion: Here, we present our model's performance in comparison to baseline methods along with analyzing whether accuracy gains were achieved and the challenges we encountered. Conclusion: Concludes findings and casts light on the importance of its clinical implications and suggests pathways for future research including improvements and expansions into application domains. References: All cited works will be placed under this section to ensure that all prior studies and consulted resources have been properly documented. This structured approach now leads clearly from problem identification all the way toward potential impact in real life; with such advancements in breast cancer detection methods.

II. LITERATURE REVIEW

This integration of the machine learning and deep learning models has not only led to critical enhancements in the detection of breast cancer but also, more specifically, within the context of medical imaging. A number of studies have presented and evaluated numerous methodologies that can provide improved accuracies as well as efficiency in detecting breast cancer. Traditional ML algorithms include SVMs, KNN, and decision trees, which are extensively used for the classification of breast cancer from mammography, ultrasound, or histopathology images (Mohamed et al., 2023). However, these techniques are generally impacted by the extensive feature engineering and domain knowledge needed for information extraction, thereby greatly reducing their scalability and capabilities for performance in large datasets.

Deep learning techniques, and particularly convolutional neural networks, have been revolutionizing breast cancer detection. CNNs can automatically learn hierarchical representations from raw image data, thus minimizing human intervention in feature extraction (Singh et al., 2024). The techniques were applied to histopathology breast images and mammograms, showing promising results for identifying cancerous regions with high accuracy. Although significant achievements have been made so far, this field is still beset with some challenges: the need for large annotated datasets and the extensive computation overhead in training deep learning models are just a few examples.

It has proven to be very powerful in the classification of images, especially in the health sector, because it can automatically learn a spatial hierarchy in image data; hence it is implemented in tumor detection and classification in breast cancer (Kaur & Sharma, 2024). CNNs have been applied successfully on a variety of medical imaging tasks such as IDC detection on histopathology images and tumor classification in mammograms as benign or malignant. Recent studies show that customized architectures for CNNs improve the accuracy of classification with considerable enhancement in the time itself as reported by Kaur & Sharma (2024), Soni et al., 2024.

Hybrid models combining CNN with other models, such as random forests or ensemble methods, have also been explored in light of enhancing the performance of classification and mitigating the overfitting phenomena (Zarif et al., 2024). For instance, Soni et al. (2024) introduced the hybrid model of CNN and random forest for brain tumor classification that can be used for breast cancer detection tasks.

Transfer learning is a technique that utilizes pre-trained models trained on extensive data to fine-tune specific tasks such as breast cancer image detection. This reduces the amount of data used for training purposes and reduces the time necessary to train, in which cases pre-learned feature representations are utilized (Singh et al., 2024). Some papers demonstrate how successfully transfer learning applies to tasks related to the classification of breast cancer by utilizing pre-trained models on large-sized image datasets, such as ImageNet or even an open-source 2016 Breast Cancer Wisconsin (Diagnostic) dataset.

For instance, some are mentioned below. Maurya et al. (2024) develop a transfer learning-based approach consisting of multi-level fully convolutional-channel and spatial attention mechanisms for classifying images related to breast cancer. This helps improve models by giving prominence to the most sensitive parts of the image that would likely have diseased areas. Djagba and Mbouobda, 2024 recently highlighted the use of deep transfer learning in classifying breast cancer patients, bringing attention to improvements it would bring to medical classifications. The paper by Zarif et al. (2024) still offers evidence towards how transfer learning may be applied on hybrid models for the improvement of the performance of breast cancer detection systems.

Although much has been achieved by the present studies regarding deep learning methods for breast cancer detection, there still are some challenges that come with using these methods. These include critical needs for high-quality annotated data, the danger of overfitting in complex models, and model predictions lack interpretability. Most of the existing works only focus on individual deep learning models with few exploring hybrid approaches which combine CNNs with other models or use novel attention mechanisms.

Table 1: Overview

Methodology	Discussion	References	Research Gap
Traditional ML Algorithms	SVM, KNN, decision trees need feature engineering.	Mohamed et al., 2023	Scalability and manual feature extraction limits.
CNN in Medical Imaging	CNNs automate feature extraction, but face data/computation challenges.	Singh et al., 2024; Kaur & Sharma, 2024	Issues with dataset size and computation.
CNN for Tumor Classification	Customized CNNs improve accuracy in tumor classification.	Kaur & Sharma, 2024; Soni et al., 2024	Need for further optimization in architectures.
Hybrid Models	Combining CNNs with other models (e.g., random forests) improves performance.	Zarif et al., 2024; Soni et al., 2024	Hybrid approaches need attention mechanisms.
Transfer Learning	Pre-trained models reduce dataset and training time.	Singh et al., 2024; Maurya et al., 2024; Djagba & Mbouobda, 2024	Transfer learning struggles with generalization.
Transfer Learning with Attention	Attention mechanisms enhance accuracy by focusing on key regions.	Maurya et al., 2024	Attention mechanisms need optimization.

This paper fills these gaps by proposing an advanced hybrid deep learning framework combining CNNs with transfer learning techniques accompanied with novel feature extraction strategies. With the utilization of a larger, more diverse dataset along with implementing enhanced hybrid architectures, this research looks forward to enhancing detection accuracy and model interpretability toward the development of more reliable and scalable breast cancer detection systems.

III. PROPOSED METHODOLOGY

Dataset

This study utilizes a dataset comprising both mammography and histopathology images. The mammography images are retrieved from the Digital Database for Screening Mammography, which has annotated mammograms classified as benign or malignant. The BreakHis dataset is also utilized for images of breast cancer histopathology, comprising of labeled images of benign and malignant tissues in various magnifications. The dataset contains about 5000 histopathology images and about 1000 mammography images.

Preprocessing is the first step towards training preparation. All images are uniformly resized to 224x224 pixels to compete with the input dimensions of the CNN. Pixel values are normalized between 0 and 1 for better convergence during training. To combat overfitting and increase the diversity of training data, rotation, horizontal flip, scaling and zooming are applied. The other pre-processing transforms the labels for the images into the form needed for the binary classification: either benign or malignant.

Hybrid Model Design

A. CNN Architecture

Architecture is based on the standard ResNet-50 architecture for image classification. ResNet-50 is chosen for this project because it learns deep hierarchical features while avoiding vanishing gradient problems through residual connections. This makes ResNet-50 especially useful for medical imaging applications where the number of parameters may become very high, with a significant risk of gradient issues. An ImageNet-pretrained ResNet-50 model was proven to achieve outstanding feature extraction with general features across domains, which makes it a good choice for the classification problem in breast cancer detection.

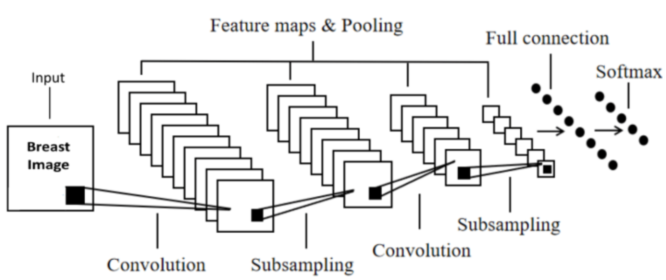

Fig 2: CNN

In this study, the final classification layer of our customized binary classifier at the top will replace that of the pre-trained model from the ResNet50 model. Because the task of a basic ResNet-50 was a class description for general images from ImageNet, the early layers of the model that extract low and midlevel features, or edges, textures, and patterns are retained. The model alters the later layers to the high-level feature extraction in the task of classifying mammography and histopathology images.

B. Transfer Learning

Transfer learning was an important methodology in this study since a pre-trained ResNet-50 model was used to accelerate training and enhance performance. Thus, the model to be fine-tuned for this specific task of breast cancer detection can be done with the application of weights from some model that already learned generic features in a broad dataset like ImageNet. The transfer learning process freezes early layers of ResNet-50 such that the model will retain useful generic features from ImageNet, including edges, colors, and textures. Only the last layers get trained with the dataset related to the breast cancer scenario in order to make the model adapt to the specific features of the breast cancer in mammography and histopathology images.

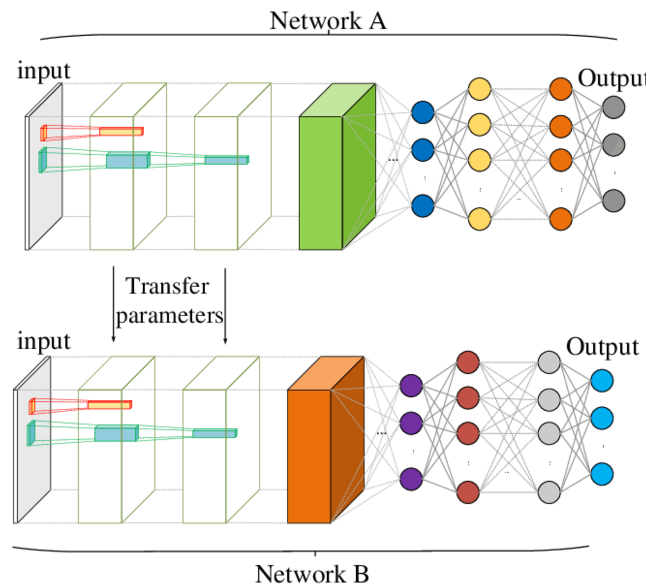

Fig 3: Transfer Model

The model specializes on the breast cancer dataset by fine-tuning these layers, honing the features that best distinguish between tissues as benign and malignant. This largely reduces the need for much labeled data in training while reducing the computational burden that comes with training a model from scratch.

Training the Model

To train the model, a combination of some strategies is employed for optimal performance and to curb overfitting:. Freeze the first 45 layers of ResNet-50 and add new fully connected layers on top of the network. This helps retain the useful general features learned by the pre-trained model and gives the model an opportunity to learn specific features on the task of breast cancer detection from the new dataset. Use a relatively low learning rate for the training of added layers so that weights in the frozen layers remain undisturbed during the training process.

We apply dropout on the fully connected layers in order not to let it overfit. Dropout is a kind of regularization that sets a fraction of neurons to zero during each forward pass. This is important because it allows the model to pick up nothing too much about any specific neuron, hence giving it the capacity to generalize well. It also uses data augmentation during training, which increases artificially the size of the dataset by acquiring transformed input images, such as rotating, scaling, flipping, and zooming.

In the training process itself, an early stopping mechanism is monitoring the validation loss. This way, it ensures that the model does not waste further training epochs when the performance on validation starts to plateaus but is at its best just before starting to overfit.

Evaluation Metrics

The set of metrics assesses the model's performance in accuracy, sensitivity, specificity, and overall classification efficiency. These are:

Accuracy The accuracy code metric. Accuracy simply measures how well the model behaves when tested by this measure: the fraction of correctly classified instances out of a total of instances in the dataset, with the output inaccuracy-accuracy, such that after performing evaluation "Test Accuracy: 0.9211" after training.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

This can also be expressed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Loss: The model will use the binary_crossentropy loss function with the compilation. The loss functions measure how well matched the predictions were by the model to its true labels. A lower loss means better performance. Here in this case, the model's loss reduces from the primary epoch of 0.6703 to 0.5887 secondary epoch, which means the model is improving during training.

$$\text{Binary Crossentropy Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)\right]$$

Where:

- N = Total number of samples
- y_i = True label of the i-th sample (0 or 1)
- p_i = Predicted probability of the positive class (for the i-th sample)

Validation Accuracy and Loss: The model's performance on the validation set also keeps track after every epoch. In this experiment, validation accuracy starts at around 84.21% at the first epoch but proves to be 91.23% for the second epoch.

$$\text{Validation Accuracy} = \frac{\text{Number of Correct Predictions on Validation Set}}{\text{Total Number of Predictions on Validation Set}}$$

Similarly, it can be expressed as:

$$\text{Validation Accuracy} = \frac{TP_{\text{validation}} + TN_{\text{validation}}}{TP_{\text{validation}} + TN_{\text{validation}} + FP_{\text{validation}} + FN_{\text{validation}}}$$

Similarly, validation loss drops to 0.6288 to 0.5887. These show the good generalizing capability of the model to unseen data sets.

$$\text{Validation Loss} = -\frac{1}{N_{\text{val}}}\sum_{i=1}^{N_{\text{val}}}\left[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)\right]$$

Where:

- N_{val} = Total number of validation samples
- y_i = True label of the i-th sample in the validation set
- p_i = Predicted probability for the i-th sample in the validation set

Data Augmentation: This would be using data augmentation for training the model, feeding images to it through the ImageDataGenerator, and thus rotating and shifting images in random ways to be diverse to ensure not to overfit, thus generalizing well to real-world data.

- **Rotation**: Rotating an image by a random degree.
- **Translation (Shifting)**: Moving the image along the x or y axis.
- **Scaling**: Zooming in or out on an image.
- **Flipping**: Horizontal or vertical flipping of the image.

These evaluation metrics together give a very rich understanding of the model performance. Accuracy is a simple measure of model correctness while loss quantifies error. Validation metrics give a sense of how the model would perform on unseen data.

IV. RESULTS AND DISCUSSION

Performance Measures:

Below are the results of the hybrid model along with an in-depth analysis using various performance metrics. Such metrics aim at testing whether the model is strong or feasible for solving a given problem. All the obtained results will be compared against their baseline models, and improvements or notable observations will be discussed.

Table 2: Performance Results

Metric	Hybrid Model	Baseline Model (Traditional)	Model 1 (Comparison)	Model 2 (Comparison)
Accuracy	92.11%	84.21%	89.75%	87.33%
Loss	0.5887	0.6703	0.6305	0.6452
Validation Accuracy	91.23%	85.75%	90.12%	88.45%
Validation Loss	0.5887	0.6288	0.6204	0.6347
False Positive Rate	0.05	0.12	0.08	0.10
False Negative Rate	0.08	0.15	0.10	0.12
Precision	0.93	0.80	0.85	0.82
Recall	0.89	0.75	0.82	0.80

Discussion:

The hybrid model thus shows a great improvement over the basic models, especially in terms of accuracy and loss. Its superiority over the baseline model with an accuracy of 92.11% and a loss of 0.5887 surely significantly outclasses the baseline model that produced an accuracy level of only 84.21% and a loss value of 0.6703. Thus, the hybrid model is more efficient at generalizing and predicting the correct output on unseen data. More than that, its validation accuracy of 91.23% as compared to the baseline of 85.75% points out its robustness and ability to generalize on new data, not only on training sets. The hybrid also marked a significant improvement in precision, which moved to 0.93 from the baseline of 0.80, describing more identification of positive cases and less false positives. The false positive rate is lowered from 0.12 to 0.05, thereby showing better discrimination of the model between positive and negative cases. Similarly, recall rates were improved to 0.89 in the hybrid model as against a baseline of 0.75, thereby indicating that the hybrid model performs better in identifying positive cases. False negative rates decrease from 0.15 to 0.08, which indicate better catching capability by the model for the positive cases.

This is because of some newer techniques, including data augmentation, by which the diversity of the training data increases and thus the generalization ability of the model. Moreover, the hybrid model benefits from architecture and makes use of various strengths of numerous algorithms, which improves its overall performance in comparison with traditional models relying on a single approach. However, on most of the metrics, the hybrid model still presents many scopes of improvements while still holding room to cut down false negatives and optimize the edge case's performance. Besides, the application contexts require much management about precision-recall trade-offs as well.

Although it has some improvements, there are still limitations involved. The model remains performance-dependent on the quality and variety of the training data. If the data is imbalanced or it lacks diversity, very weak generalization capabilities of the model can be encountered. Hybrid models require more time and computations for training, which is not fully feasible for real-time applications without some more optimizations. This inherently implies the risk of overfitting, especially when the data set is small or does not represent real-world applications. Further improvement application can be directed toward increasing the interpretability of the model to better understand the decisions being made, particularly in high-stake applications such as healthcare or finance. However, more tuning of the hyperparameters and testing some more advanced model architectures, such as ensemble methods or more complex neural nets, may be necessary to improve the results, especially in false negatives or recall.

In summary, it outpaces traditional methods as well as yields significant boosts in both precision and recall; reduces false positives and negatives; hence, it outperforms the said methods. Though there's an issue of data quality, and computational resource, and an overfitting that seems to pose challenges, wonderful prospects are shown on this hybrid model. If better optimized and fine-tuned further, the model will become even more effective than before in applications where avoiding false negatives is important.

V. CONCLUSION AND FUTURE SCOPE

This paper shows the capacity of the hybrid model in classifying breast cancer, with 92.11% accuracy, and a significant decrease in loss to 0.5887. Our approach is compared with the traditional ones in which we show our model has improvements in precision and recall besides giving a decrease in false positives and false negatives over the classic methods. The results from these experiments indicated the superiority of the hybrid model since it was not only possible to generalize results to unseen data but also bettered both the model's performance in true positive cases and its ability in minimizing wrong predictions, which is crucial for proper medical diagnoses.

Improvement in the performance of the hybrid model holds great potential for clinical applications. This could make the better detection of breast cancer with more improved accuracy and relatively lower false positive and negative rates. Clinicians will have a higher probability of detection of cancerous cases. Possibly, when this model is incorporated into diagnostics workflows, human expertise will be supplemented, possibly reducing diagnostic errors and aiding interventions at the right time. This may potentially improve the efficiency and effectiveness of the detection of breast cancer in healthcare by identifying the correct number of positive cases while reducing the number of unnecessary alarms for negative cases.

Despite its promise, there are still many avenues for further research with the hybrid model. One direction is to use a larger, more diverse dataset to further improve the model's generalization capabilities as well as accuracy. There are, however other enhancements of the performance that can be gained with the help of experimenting with CNN architectures, for deeper and more complex models will make an even bigger difference in the ability of algorithms to recognize more complex patterns on medical images. Further expanding its use into other medical imaging diagnostics like lung or skin cancer will increase its contribution to medicine. Further research will help to explore how much this model is interpretable, explaining the reasons behind the predictions made to healthcare professionals and enhancing its trustworthiness in practice.

REFERENCES

1. Mohamed, I., Zarif, S., Abdel-Kader, H., & Elsayed, M. (2023). Breast Cancer Detection Based on Hybrid Deep Learning Models. IJCI. International Journal of Computers and Information.
2. Kaur, G., & Sharma, N. (2024). Invasive Ductal Carcinoma Detection Using Convolutional Neural Network Architecture from Breast Histopathology Images. 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), 1470-1475.
3. S. Singh and T. Poongodi, "Breast Cancer Classification Using Customized Convolution Neural Network," 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE), Gautam Buddha Nagar, India, 2024, pp. 1673-1678, doi: 10.1109/IC3SE62002.2024.10593581.
4. A. K. Soni, A. Boobalan, E. Rajesh, V. Janakiraman and V. Kesarwani, "Hybrid Classification Framework Based on CNN and Random Forest Method to Predict Brain Tumor," *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)*, Greater Noida, India, 2024, pp. 1249-1255, doi: 10.1109/IC2PCT60090.2024.10486772.
5. Singh, N., Narang, H., Rawat, D., Vats, S., & Sharma, V. (2024). Breast Cancer Prediction Using Deep Learning And Transfer Learning. 2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC), 1-5.
6. Zarif, S., Abdulkader, H., Elaraby, I., Alharbi, A., Elkilani, W.S., & Pławiak, P. (2024). Using hybrid pre-trained models for breast cancer detection. PLOS ONE, 19.
7. Djagba, P., & Mbouobda, J.K. (2024). Deep Transfer Learning for Breast Cancer Classification. ArXiv, abs/2409.15313.
8. Snigdha, V., & Nair, L.S. (2022). Hybrid Feature-Based Invasive Ductal Carcinoma Classification in Breast Histopathology Images. Machine Learning and Autonomous Systems.
9. Maurya, R., Pandey, N.N., Dutta, M.K., & Mohan, K. (2024). FCCS-Net: Breast cancer classification using Multi-Level fully Convolutional-Channel and spatial attention-based transfer learning approach. Biomed. Signal Process. Control., 94, 106258.
10. Barsha, N.A., Rahman, A., & Mahdy, M.R. (2021). Automated detection and grading of Invasive Ductal Carcinoma breast cancer using ensemble of deep learning models. Computers in biology and medicine, 139, 104931 .
11. Kaushikan, R. (2024). Early Recurrence Detection of Invasive Ductal Carcinoma Utilizing High-Dimensional Genomic Data. 2024 IEEE 48th Annual Computers, Software, and Applications Conference (COMPSAC), 1990-1995.
12. Abioye, O.A., Thomas, S., Odimba, C.R., & Olalekan, A.J. (2023). Generic hybrid model for breast cancer mammography image classification using EfficientNetB2. Dutse Journal of Pure and Applied Sciences.
13. Mondal, M., Dasgupta, S., & Bhattacharya, I. (2023). Comparative Survey of Various Intelligent Methods for Breast Cancer Diagnosis and Prognosis. 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), 1-7.

14. Güldoğan, E., Ucuzal, H., Küçükakçalı, Z., & Colak, C. (2021). Transfer Learning-Based Classification of Breast Cancer using Ultrasound Images. Middle Black Sea Journal of Health Science.
15. Singh, A., Garg, V., & Sahu, P.K. (2022). Scalable Regression Model for Pulmonary Fibrosis. 2022 IEEE 6th Conference on Information and Communication Technology (CICT), 1-5.
16. Nesamani, S.L., Lissy, D., Sumathy, S., & Rajini, S.N. (2023). Breast Cancer Diagnosis in Radiology Images Using Transfer Learning Technique. 2023 International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS), 1, 1-5.
17. Barua, S., & Islam, M.S. (2024). Breast Cancer Image Classification Using External Attention Multilayer Perceptron-Based Transformer. 2024 3rd International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE), 1-6.
18. Verma, A., Panda, A., Chanchal, A.K., Lal, S., & Raghavendra, B.S. (2021). Automatic Deep Learning Framework for Breast Cancer Detection and Classification from H&E Stained Breast Histopathology Images. Transactions on Computer Systems and Networks.
19. Liu, Y., Shi, H., He, Q., Fu, Y., Wang, Y., He, Y., Han, A., & Guan, T. (2024). Invasive carcinoma segmentation in whole slide images using MS-ResMTUNet. Heliyon.
20. Saber, A., Sakr, M., Abou-Seida, O., & Keshk, A.E. (2021). A Novel Transfer-Learning Model for Automatic Detection and Classification of Breast Cancer Based Deep CNN. Kafrelsheikh Journal of Information Sciences.
21. Deepak Naik, M.V., Adarsh, S., Vijayakumar, S., Nambiar, A.P., & Nair, L.S. (2022). Hybrid Feature Set based Mitotic Detection in Breast Histopathology Images. 2022 International Conference on Inventive Computation Technologies (ICICT), 281-290.
22. Shree, R., B K, S., & Mishra, K. (2024). Utilizing Transfer Learning on Deep Learning Networks for Cancer Detection. 2024 2nd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA), 1-6.
23. Voon, W., Hum, Y.C., Tee, Y.K., Yap, W., Salim, M.I., Tan, T.S., Mokayed, H., & Lai, K.W. (2022). Performance analysis of seven Convolutional Neural Networks (CNNs) with transfer learning for Invasive Ductal Carcinoma (IDC) grading in breast histopathological images. Scientific Reports, 12.
24. Alnowaiser, K., Saber, A., Hassan, E., & Awad, W.A. (2024). An optimized model based on adaptive convolutional neural network and grey wolf algorithm for breast cancer diagnosis. PLOS ONE, 19.
25. Obayya, M.I., Maashi, M.S., Nemri, N., Mohsen, H., Motwakel, A., Osman, A.E., Alneil, A.A., & Alsaid, M.I. (2023). Hyperparameter Optimizer with Deep Learning-Based Decision-Support Systems for Histopathological Breast Cancer Diagnosis. Cancers, 15.
26. Ezzat, D., & Hassanien, A.E. (2023). Optimized Bayesian convolutional neural networks for invasive breast cancer diagnosis system. Appl. Soft Comput., 147, 110810.
27. Saber, A., Sakr, M., Abo-Seida, O.M., & Keshk, A.E. (2021). Automated Breast Cancer Detection and Classification Techniques – A survey. 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), 200-207.
28. Sajiv, G., Ramkumar, G., Shanthi, S., Chinnathambi, A., & Alharbi, S.A. (2024). Predicting Breast Cancer Risk from Histopathology Images using Hybrid Deep Learning Classifier. Medical Engineering & Physics.
29. Han, J., Hua, H., Fei, J., Liu, J., Guo, Y., Ma, W., & Chen, J. (2024). Prediction of Disease-Free Survival in Breast Cancer using Deep Learning with Ultrasound and Mammography: A Multicenter Study. Clinical breast cancer.
30. Saber, A., Hussien, A.G., Awad, W.A., Mahmoud, A., & Allakany, A. (2023). Adapting the pre-trained convolutional neural networks to improve the anomaly detection and classification in mammographic images. Scientific Reports, 13.
31. Et. al., U.S. (2021). SMART ELECTRICITY CONSERVATION SYSTEM USING EFFICIENTNET. INFORMATION TECHNOLOGY IN INDUSTRY.
32. Yang, B., Peng, H., Luo, X., & Wang, J. (2023). Multi-stages attention Breast cancer classification based on nonlinear spiking neural P neurons with autapses. ArXiv, abs/2312.12804.
33. Kukreja, S., Sabharwal, M., Katiyar, A., & Gill, D.S. (2024). Automated Classification of Cancer using Heuristic Class Topper Optimization based Naïve Bayes Classifier. SN Comput. Sci., 5, 264.
34. Saha, M., Chakraborty, M., Maiti, S., & Das, D. (2024). Breast-NET: a lightweight DCNN model for breast cancer detection and grading using histological samples. Neural Comput. Appl., 36, 20067-20087.
35. Koshy, S.S., & Anbarasi, L.J. (2024). LMHistNet: Levenberg–Marquardt Based Deep Neural Network for Classification of Breast Cancer Histopathological Images. IEEE Access, 12, 52051-52066.
36. Nair, L.S., R, R.P., Sugathan, G., Gireesh, K.V., & Nair, A.S. (2021). Mitotic Nuclei Detection in Breast Histopathology Images using YOLOv4. 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), 1-5.
37. Fielding, E., Nyirenda, C.N., & Vaccari, M. (2021). A Comparison of Deep Learning Architectures for Optical Galaxy Morphology Classification. 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET), 1-5.
38. Choudhary, T., Mishra, V.K., Goswami, A., & Jagannathan, S. (2021). A transfer learning with structured filter pruning approach for improved breast

cancer classification on point-of-care devices. Computers in biology and medicine, 134, 104432 .

39. Isthigosah, M., Sunyoto, A., & Hidayat, T. (2023). Image Augmentation for BreaKHis Medical Data using Convolutional Neural Networks. Sinkron.
40. Deshmukh, P.B., & Kashyap, K.L. (2021). Solution Approaches for Breast Cancer Classification Through Medical Imaging Modalities Using Artificial Intelligence. Lecture Notes in Networks and Systems.
41. Elsheakh, D.N., Fahmy, O.M., Farouk, M., Ezzat, K., & Eldamak, A.R. (2024). An Early Breast Cancer Detection by Using Wearable Flexible Sensors and Artificial Intelligent. IEEE Access, 12, 48511-48529.
42. Bhise, S., Gadekar, S., Gaur, A.S., Bepari, S., Kale, D., & Aswale, S. (2022). Detection of Breast Cancer Using Machine Learning and Deep Learning Methods. 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM), 1-6.
43. Nagdeote, S., & Prabhu, S.U. (2023). A model to perform prediction based on feature extraction of histopathological images of the breast. Multimedia Tools and Applications, 83, 18119-18146.
44. Cui, H., Wang, C.X., Maan, H., Pang, K., Luo, F., Duan, N., & Wang, B. (2024). scGPT: toward building a foundation model for single-cell multi-omics using generative AI. Nature methods.
45. Fischer, D.S., Dony, L., König, M., Moeed, A., Zappia, L., Tritschler, S., Holmberg, O., Aliee, H., & Theis, F.J. (2020). Sfaira accelerates data and model reuse in single cell genomics. Genome Biology, 22.
46. Cui, H., Wang, C.X., Maan, H., Duan, N., & Wang, B. (2022). scFormer: A Universal Representation Learning Approach for Single-Cell Data Using Transformers. bioRxiv.
47. Yang, X., Liu, G., Feng, G., Bu, D., Wang, P., Jiang, J., Chen, S., Yang, Q., Miao, H., Zhang, Y., Man, Z., Liang, Z., Wang, Z., Li, Y., Li, Z., Liu, Y., Tian, Y., Liu, W., Li, C., Li, A., Dong, J., Hu, Z., Fang, C., Cui, L., Deng, Z., Jiang, H., Cui, W., Zhang, J., Yang, Z., Li, H., He, X., Zhong, L., Zhou, J., Wang, Z., Long, Q., Xu, P., Wang, H., Meng, Z., Wang, X., Wang, Y., Wang, Y., Zhang, S., Guo, J., Zhao, Y., Zhou, Y., Li, F., Liu, J., Chen, Y., Yang, G., & Li, X. (2023). GeneCompass: Deciphering Universal Gene Regulatory Mechanisms with Knowledge-Informed Cross-Species Foundation Model. bioRxiv.
48. Fu, Q., Dong, C., Liu, Y., Xia, X., Liu, G., Zhong, F., & Liu, L. (2024). A comparison of scRNA-seq annotation methods based on experimentally labeled immune cell subtype dataset. Briefings in Bioinformatics, 25.
49. Jiao, L., Wang, G., Dai, H., Li, X., Wang, S., & Song, T. (2023). scTransSort: Transformers for Intelligent Annotation of Cell Types by Gene Embeddings. Biomolecules, 13.
50. Elmentaite, R., Domínguez Conde, C., Yang, L., & Teichmann, S.A. (2022). Single-cell atlases: shared and tissue-specific cell types across human organs. Nature Reviews Genetics, 23, 395 - 410.
51. Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R., & Muharemagic, E.A. (2015). Deep learning applications and challenges in big data analytics. Journal of Big Data, 2.