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PAPER

Hyperparameter Optimisation for Breast Cancer Detection Using APO and Pre-Trained CNNs

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ABSTRACT

Early detection of breast cancer improves survival rates and treatment outcomes. Mammography remains the key diagnostic technique; however, building deep learning models for reliable categorisation is challenging. This paper presents a groundbreaking method for fine-tuning hyperparameters in two cutting-edge convolutional neural networks (CNNs), ConvNeXtBase and ResNet-50, which employ the Arctic Puffin Optimisation (APO) algorithm. Experiments were performed on two benchmark mammography datasets: CBIS-DDSM and MIAS. The APO-optimised ConvNeXtBase model achieved 98.46% accuracy on the CBIS-DDSM dataset and 99.34% on the MIAS dataset, with precision and recall both at 100% in the latter. These findings indicate that APO increases CNN performance, making it a promising tool for computer-assisted breast cancer diagnosis.

KEYWORDS

arctic puffin optimisation (APO), breast cancer, convolutional neural networks (CNNs), deep learning, transfer learning

1 INTRODUCTION

Breast cancer is the most commonly diagnosed cancer in women, but men can get it, too. Breast cancer affects approximately one out of every eight women in the United States at some point in their lives, as reported by [1, 2]. It is expected that around 310,720 new cases of invasive breast cancer will be discovered in the US by 2024, with 16% of these instances involving women under the age of 50. Furthermore, it is projected that 56,500 women will be diagnosed with ductal carcinoma in situ (DCIS) in the same year [3, 4]. Although advances in early identification and treatment have resulted in lower death rates, the incidence of breast cancer has grown by around 1% per year since 2012. Racial disparities persist, with Black women experiencing a mortality rate that is 38% higher than that of white women, despite having a 5% lower incidence rate [1]. Globally, the 5-year survival rate for localised breast cancer exceeds 80% in high-resource settings but falls between

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10% and 40% in low-resource environments [5, 6]. Various imaging techniques are used to aid in the early diagnosis of breast cancer. Mammography is considered the standard examination procedure. This technology uses low-dose X-ray beams to make pictures of the breast, which aids in the detection of breast cancer [7, 8]. Recently, much research presented concerns about methods and techniques of identifying breast cancer in its early stages. Deep learning methods are gaining traction in breast cancer classification because they enable Computer Aided—Diagnostic (CAD) models to assist radiologists in accurately analysing suspicious lesions. Deep-learning methods like convolutional neural network (CNN) reduce human error and prejudice by automatically extracting features. CNNs are a deep learning method. CNN designs struggle to acquire and recall a lot of visual information, limiting their ability to screen for breast cancer [9, 10]. Optimising several parameters and picking the best CNN architecture is complex and time-consuming. In their efforts to solve these problems, researchers have found that population-based algorithms are helpful. GA and PSO solve large search region problems as population-based algorithms. Both algorithms are "population-based". GA and PSO are bio-inspired metaheuristics that may solve challenging optimisation problems [11]. Another example is genetic algorithms. Both algorithms are genetic. This study optimises CNN parameters using Arctic Puffin Optimisation (APO). Thus, algorithm implementation achieves this. Watching Arctic puffins survive and forage helps explain the difficult balance between exploration and exploitation. The application also simulates a puffin's aerial searches during exploration to find other options. Puffins' focused foraging during exploitation partly dictates the hyperparameter values. This is true regardless of hyperparameters. APO uses an adjustable search technique to find CNN architectures. This method creates durable, cost-effective models. Feature-based learning and fine-tuning training can facilitate transfer learning. Only the last levels receive new information through feature-based transfer learning, which uses trained model layers as feature extractors. The goal is to streamline learning. Extra layers can be fine-tuned to match fresh data. This method is possible. This project implements transfer learning using ResNet-50 and ConvNeXtBase CNN architectures. By replacing layers completely tied to the most efficient architecture, APO finds optimal configurations. This approach improves model performance and generalisation.

This paper delineates the subsequent main contributions:

- The first application of APO for CNN hyperparameter tuning in breast cancer classification.
- A demonstration that APO outperforms traditional metaheuristics like PSO, GWO, and MPA in deep learning optimisation tasks.
- Improved model generalisability via stringent data augmentation to address class imbalance and enhance feature learning.
- A comprehensive evaluation of MIAS and CBIS-DDSM datasets to validate performance and practical applicability.

2 RELATED WORKS

In this section, research that used deep learning to diagnose breast cancer using mammogram images is demonstrated based on the Curated Breast Imaging Subset of the Digital Database for Screening—Mammography (CBIS-DDSM), Mammographic Image Analysis—Society (MIAS), and Digital Database for Screening Mammography

(DDSM) datasets. Authors in [12] A breast abnormality CADx system emerged through the methods of transfer and ensemble learning. EfficientNet together with ResNet provided solutions for overcoming limitations that CBIS-DDSM data presented. The method of soft voting combined with ensemble learning techniques both enhanced prediction classification performance and system reliability. The two-stage model of ensemble approaches in breast cancer systems reaches 96.05% abnormality type identification while showing 85.71% accuracy in pathology diagnostics. In [13], a CAD system for breast cancer uses Deep CNN (DCNN) models and Support Vector Machines (SVM) classifiers to improve diagnostic accuracy. Fine-tuning DCNN designs like AlexNet, GoogleNet, and ResNet for end-to-end classification yielded 76.01% accuracy with GoogleNet in four experiments. Extracting deep features from each model and classifying them using SVMs increased accuracy to 93.7% with ResNet-18 features. After fusing deep data from various DCNNs to form merged feature sets, SVMs achieved 97.9% accuracy on the largest fusion set. The fourth experiment reduces features using principal component analysis (PCA). CAD breast cancer diagnosis performance can be considerably improved by merging various DCNN features with SVM classification and dimensionality reduction algorithms. A deep-learning model is created in [14] for breast cancer classification based on mammography images from the MIAS dataset. The model uses pretrained CNNs, such as VGG16, ResNet50, and InceptionV3, to categorise pictures as benign, malignant, or normal. They used preprocessing techniques including noise reduction and histogram equalisation to increase image quality while reducing calculation time. The model obtained the area under curve (AUC) of 0.995 and 98.96% accuracy using VGG16, demonstrating the efficacy of transfer learning in medical picture categorisation. In [15], the authors developed a CNN model for the automated detection of breast cancer. This model combines mammogram and ultrasound images from four datasets: BUS1-2, Inbreast, MIAS, and DDSM. The model has a basic design with four convolutional layers and one fully connected layer, which helps to reduce both the number of parameters and the processing costs. We employed data augmentation approaches to address overfitting and class imbalance. The model obtained 96.55% accuracy on the 100% on BUS-1, and 89.73% on BUS-2, MIAS dataset, 90.68% on DDSM, and 91.28% on Inbreast, exceeding other recent CAD systems due to its strong accuracy and efficiency across many imaging modalities. The mini-MIAS dataset was used to create a MultiscaleAll CNN (MA-CNN) that classified mammography images as normal, malignant, or benign in [16]. The MA-CNN enhances classification accuracy by employing multiscale dilated convolutions, whilst typical pooling is substituted by larger-stride convolutions to reduce computing costs. Preprocessing methods increase picture quality; however, data augmentation may result in class imbalances. The MA-CNN achieves 96.47% accuracy, 96% sensitivity, and an AUC of 0.99, exceeding standard convolutional networks in both efficiency and diagnostic efficacy. The author in [17] proposes a hybrid deep learning model that enhances mammography breast cancer diagnosis using Radon transform, data augmentation, and CNN architecture. The Radon transform gives mammograms a time–frequency structure for enhanced feature extraction, and data augmentation balances datasets with image variants. Four convolutional blocks and fully linked layers gave this hybrid CNN 99.17% MIAS and 98.44% DDSM accuracy. UNet-CNNs could improve border segmentation in future studies; however, morphological segmentation distinguishes cancer regions. The method's high sensitivity and specificity suggest radiologists might automatically diagnose clinical breast cancer. On the other hand, researches that used deep learning and bio-inspired optimisation approaches to diagnose breast cancer using mammogram images is introduced. For example, some researchers used metaheuristic algorithms as optimisers as in [18, 19, 20], for the MIAS, DDSM, and CBIS-DDSM datasets. Authors in [18] developed a diagnostic model that optimises hyperparameters with a hybrid CNN and Improved-Marine-Predators Algorithm (IMPA). The IMPA-ResNet50 architecture achieved an accuracy of 98.88% on the MIAS and 98.32% on the CBIS-DDSM. In [19] an advanced breast cancer diagnostic model uses modified DenseNet-121 and VGG-16 CNN architectures. Bidirectional Long Short-Term Memory (BiLSTM) layers and machine learning classifiers like Support Vector Memory (SVM) and Random Forest (RF) replace CNNs' fully linked layers. SVM and RF algorithms speed up feature capture and categorisation. Grey Wolf Optimisation (GWO) refined CNN and classifier hyperparameters. With VGG-16 added to SVM, this model had 99.86% MIAS accuracy, 99.4% INbreast accuracy, and a near-perfect AUC of 1.0. CNN feature extraction with improved machine learning classifiers aids breast cancer diagnosis. In [20] a CNN model with PSO improves mammography breast cancer classification. PSO optimises CNN kernel size, stride, and filters for DDSM and MIAS mammography datasets. Data augmentation and contrast-restricted adaptive histogram equalisation increased model performance. The Particle Swarm Optimisation Convolutional Neural Networks (PSOCNN) model outperformed CNNs without optimisation on the DDSM and MIAS datasets with 98.23% and 97.98% accuracy. These results show that PSO optimises CNN hyperparameters for breast cancer diagnosis. CNN optimisation utilising metaheuristic methods with diverse datasets is described in [21] and [22]. In [21], CNN architectures are optimised using bio-inspired algorithms PSO and GA to detect early breast cancer in infrared pictures. The work optimises hyperparameters for the fully connected DenseNet-201, ResNet-50, and VGG-16 layers. The findings show thermography's non-invasive diagnostic potential and bio-inspired optimisation's ability to improve CNN performance for medical imaging. [22] shows how PSO and ANN might improve breast cancer diagnosis. ANN weights are improved by the PSO, improving classification accuracy and minimising processing complexity. This technique outperformed ANN models on the Wisconsin dataset with 95% accuracy. Model performance confirms the ANN-PSO approach's strong and automatic breast cancer classification.

This study demonstrates the first application of APO for hyperparameter tuning of CNNs in breast cancer diagnosis using mammographic images. Metaheuristics like PSO, GWO, and MPA are less adaptive and efficient than our search technique. APO balances exploration and exploitation better than PSO and GWO, which converge early. Adjustable step sizes and puffin-inspired behavioural transitions help avoid local minima and explore solution spaces. MPA's rigid movement patterns impede flexibility in high dimensions. APO uses sophisticated transfer learning models ResNet50 and ConvNeXtBase, plus data augmentation and class balancing. This novel approach outperforms benchmark dataset categorisation and generalisation approaches. Based on the success of APO's deep learning-based medical image analysis, this study guides CNN architecture optimisation for breast cancer detection.

3 METHODOLOGY

Figure 1 shows the suggested research framework: data preparation, augmentation, division, and APO-based CNN hyperparameter tuning. APO and transfer learning models improve modular pipeline classification accuracy, efficiency, and scalability. The graphic shows our system's key phases, from input data to performance evaluation.

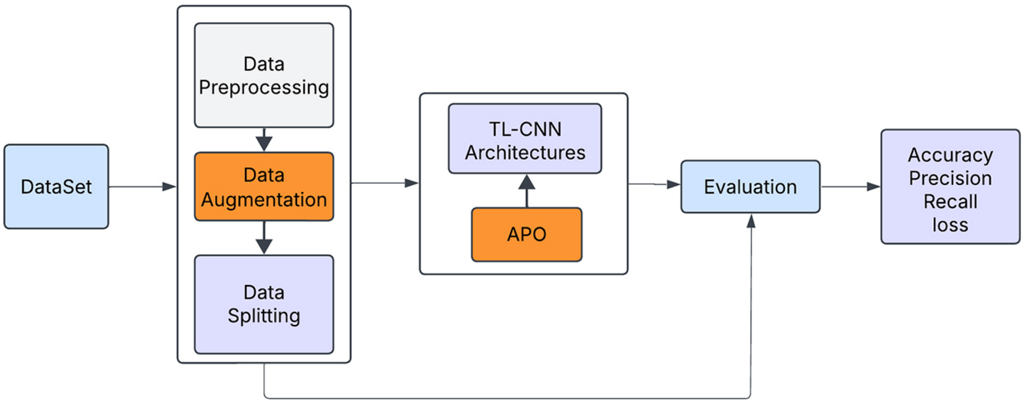

Fig. 1. Flowchart of the suggested breast cancer classification framework

3.1 Dataset

In this study, multi-modal breast cancer datasets were used, notably the mammography datasets MIAS and CBIS-DDSM [23, 25]. These datasets were used to train and evaluate the proposed framework, allowing for detailed analysis of pictures with varying resolutions, tissue density, and lesion characteristics. The MIAS (Mammographic Image Analysis Society) dataset is commonly utilised in breast cancer research. It consists of 330 digitised mammography images. Each image was resized to 1024×1024 pixels at a 200-micron resolution. The database includes 208 benign and 114 malignant cases. The distribution of benign and malignant cases provides a credible estimate of case frequency, which is useful for future studies. Each mammography image represents either the left or the right breast, resulting in a matched dataset for complete analysis [24]. We used the (CBIS-DDSM) in the experiments [26, 27]. This dataset contains 10,704 mammographic images divided into mass, calcification, and null instances. The images, which were initially obtained from normal mammography equipment [28], provide critical region-of-interest segmentation and pathologic diagnoses that enable studies in computer-aided detection and diagnosis. We used preprocessing techniques to ensure uniformity and improve the quality of mammographic characteristics. The dataset includes 5,088 mass images, 5,010 calcification images, and 606 null cases, giving a clear overview of the dataset's structure. The calcification category was the focus of this study. It has 1,588 full mammograms, with 1,018 being benign, 570 being malignant, and 284 being null. This lets us test our breast cancer detection model in a wide range of situations.

3.2 Pre-processing

We apply several preprocessing steps to enhance data quality, consistency, and model performance, ensuring the datasets are in optimal form for training and testing. Data cleaning is performed to remove errors, missing values, and irrelevant data, ensuring the reliability of the analysis. Data labelling involves annotating raw mammography images with meaningful labels for accurate classification. Data scaling standardises image dimensions by resizing the images to 224×224 pixels with three colour channels, ensuring uniformity and compatibility across deep learning architectures. Using augmentation, class weighting, and hierarchical classification, data balancing fixes class imbalances. These methods make the model more general and reduce bias. Finally, data shuffling is applied to randomise the sample order, preventing the model from learning unintended patterns from sequential data and thereby enhancing its robustness and predictive performance.

3.3 Data augmentation

Deep learning applications need well-balanced large datasets for reaching their optimal model performance. Medical imaging datasets generally contain poorly balanced classes as well as small-quantity specimens that both limit model generalisation capabilities and promote overfitting. Different data augmentation methods helped us solve these problems by creating a diverse training dataset which improved model training performance [29]. The purpose of these transformations consists of rotation and flipping as well as contrast modifications to produce a more comprehensive dataset. Such an approach matches well with dealing with both unbalanced and limited medical datasets. The approach provides deep learning models with adequate training data, including multiple samples that help them achieve better classification performance.

3.4 Data splitting

Dataset splitting starts only after the preprocessing task finishes. Depended on related works to guide the data-splitting process, where 70% of data serves training purposes and 30% functions for testing which will later be used with deep learning algorithms in classification operations.

3.5 CNN-based pre-trained models

Deep learning, particularly CNNs [30], has become essential in medical image analysis due to their ability to extract features without human intervention. However, CNNs require extensive data labelling, which is often limited in medical datasets, leading to overfitting and poor generalisation. To address this, data augmentation is employed to expand dataset size artificially, while transfer learning leverages pre-trained CNNs [31, 32], such as ConvNeXtBase [33], to adapt learnt features from large datasets like ImageNet to specific medical applications. ConvNeXtBase, a modernised CNN introduced in 2022, incorporates enhanced convolutions, inverted bottlenecks, and LayerNorm, improving efficiency and accuracy. Pre-trained on ImageNet-1K, it demonstrated high classification performance, making it a strong candidate for breast cancer diagnosis. In this study, the ConvNeXtBase model is fine-tuned by modifying the final layer for binary classification and adjusting training layers to optimise learning for mammography images, ensuring improved feature extraction and classification accuracy.

3.6 APO

The APO algorithm is an advanced metaheuristic technique inspired by the adaptive foraging behaviour of Arctic puffins. It balances exploration and exploitation through two key strategies: aerial flight and underwater foraging. The exploration phase, modelled after puffins' aerial movement, utilises Lévy flight and swooping mechanisms to enhance search diversity, allowing the algorithm to escape local search. The exploitation phase, resembling puffins' underwater foraging, refines solutions by leveraging cooperative hunting and adaptive search techniques. By integrating these strategies, APO ensures efficient global optimisation, demonstrating superior adaptability, robustness, and convergence speed, making it highly effective for complex optimisation problems [34]. The configurations of APO is shown in Table 1.

Table 1. APO parameter configurations

Parameter Settings	Values
Population size	10
Maximum iterations	1
Synergy factor (F)	0.5
Search strategy transition factor (C)	0.5
Behavioural conversion factor (B)	Adaptive (based on iteration progress)

3.7 Experimental setup

This study was conducted using Python 3.10.14 on Kaggle, which had a time limit of 30 hours per week and a maximum of 12 runtime sessions. It also had access to four logical CPU cores and a GPU with 30GB of RAM. The study used the CBIS-DDSM and MIAS mammography datasets, which included high-quality Full Field Digital Mammography (FFDM) pictures that didn't require further filtering, to train and assess the model, The amount of images used is in Table 2 with the consumed setting.

Table 2. Datasets images used and the setting

Dataset	Benign	Malignant	RAM	Time
MIAS	1527	1517	30GB	12h
CBIS-DDSM	4988	4986	30GB	12h

To improve the efficacy of the pre-trained CNN model, ConvNeXtBase, using the CBIS mammography and MIAS datasets, we employed APO to adjust their hyperparameters. We set up the APO method to tweak hyperparameters over five epochs in a single tuning cycle. In each cycle, it explored a search space of 10 possible solutions while adjusting key hyperparameters to enhance model performance. This systematic approach increased the effectiveness and efficiency of model tuning by enabling a full evaluation of hyperparameter configurations. Throughout the APO optimisation process, we applied garbage collection to clear unused memory and reduce RAM consumption. Using Levy flights for broad exploration and Brownian motion for local exploitation, APO efficiently searched the hyperparameter space. After five epochs of optimisation, the settings in Table 3 were identified as optimal.

Table 3. The optimal values

Trainable Layers	Optimiser	Batch Size	Dropout	Model
8% layers	Adam	16	0.0	ConvNeXtBase

3.8 Model performance and results

After identifying the best configuration, the optimal hyperparameters were applied to ConvNeXtBase (as it demonstrated superior performance in initial trials), and the model was trained for 10 epochs on the CBISDDSM and MIAS datasets. By training over 10 epochs, the model effectively learnt the properties of each dataset while lowering overfitting and computational burden. The model's capacity is fully adjusted to subtle patterns associated with cancer diagnosis. Extended training led to considerable improvements in accuracy. Training on high-resolution mammographic images, even for 10 epochs, required considerable computational resources. Memory consumption was high, especially given the batch size and number of trainable layers. APO's memory management approach, using garbage collection, helped manage RAM usage during optimisation. However, training remained memory-intensive, with GPU/TPU utilisation consistently high due to the model's depth and the data size, particularly for CBIS-DDSM. We chose a batch size of 16 to optimise this balance, even though each epoch still required significant processing time. The consumed resources after training are shown in Table 4.

Table 4. Used resources

Dataset	Epoch	Trainable Layers	Memory	Time
CBIS-DDSM	10	13,698,050 of 88,618,114	18GB	3:17h
MIAS			17.5GB	2h

The model's classification performance on CBIS-DDSM and MIAS datasets was evaluated using key metrics and validated by equations (1) to (3) [35].

$$Recall = \frac{TP}{TP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Table 5 presents the efficacy evaluation of the proposed framework on the CBIS-DDSM dataset, calculated based on classification results from the training and testing subsets.

Table 5. Performance analysis of the CBIS-DDSM dataset

Metrics	Training	Testing
Accuracy	99.51	98.46
Precision	99.51	98.46
Recall	99.51	98.46
Loss	0.0169	0.0574

Figure 2 illustrates the performance analysis, with the model achieving 99.51% accuracy, precision, and recall during training and a low loss of 0.0169. These high scores reflect the model's strong capability to accurately learn the features of breast cancer cases within the CBIS-DDSM dataset. The model's consistently high performance during training shows it captured key patterns and achieved excellent accuracy.

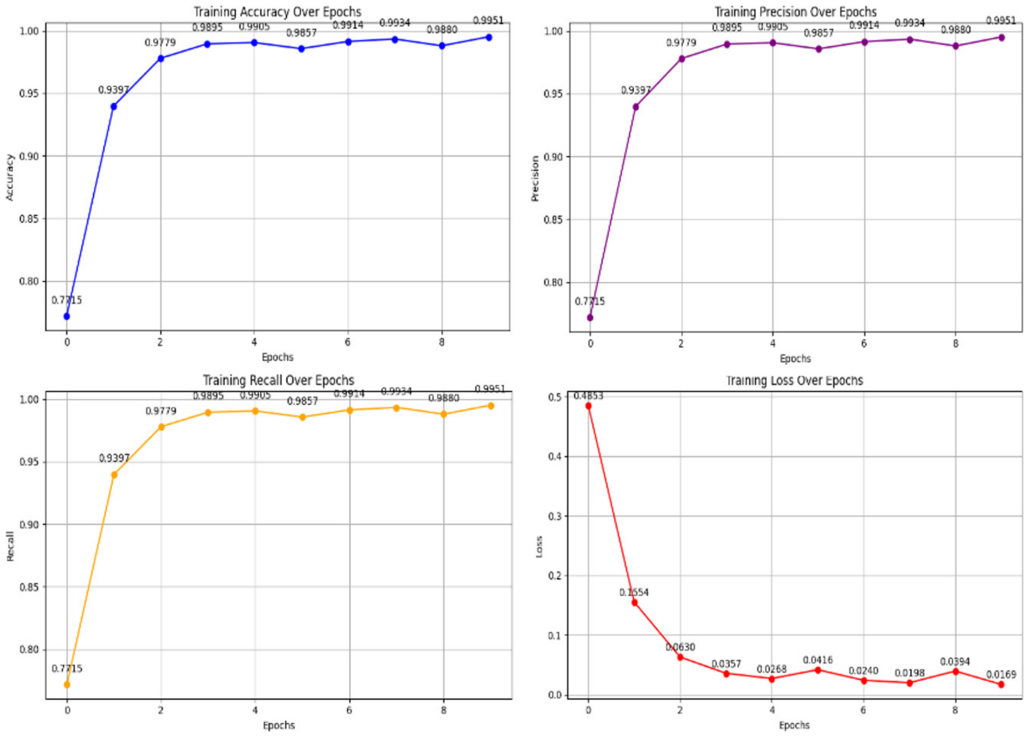

Fig. 2. Performance analysis of CBIS training

In the testing phase, as shown in Figure 3, the model continued to exhibit strong performance, achieving an accuracy of 98.46%. Precision and recall metrics both stood at 98.46%, indicating the model's reliable classification ability when applied to unseen data. The testing loss was slightly higher than during training, recorded at 0.0574, but still indicated a low error, affirming the model's effective generalisation to new samples. The small difference of 1.05% in accuracy between the training and testing phases suggests a robust model performance with minimal overfitting, showcasing its effectiveness in detecting breast cancer cases within the CBIS dataset as shown in Table 6.

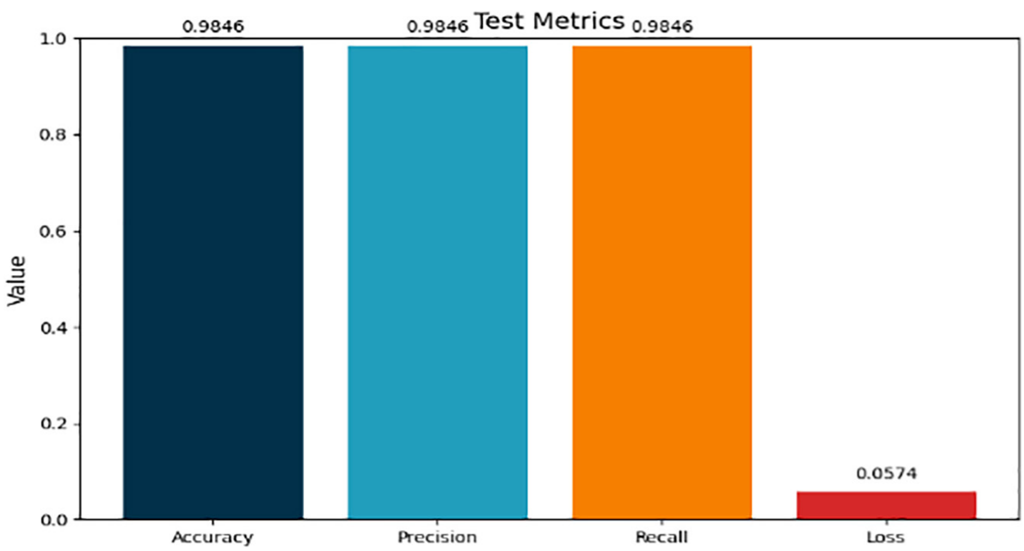

Fig. 3. Graphical bar for performance analysis of CBIS testing

Table 6. Performance analysis comparison for CBIS-DDSM

Ref	Model	Accuracy	Precision	Recall	Loss
[12]	PSOCNN	98.23	–	–	–
[10]	IMPACNN	98.32	–	–	–
	Proposed APOCNN	**98.46**	**98.46**	**98.46**	**0.0574**

The efficacy evaluation of the proposed model on the MIAS dataset is based on the classification outcomes of the training and testing subsets, as indicated in Table 7.

Table 7. Performance analysis of the MIAS dataset

Metrics	Training Set	Testing Set
Accuracy	100	99.34
Precision	100	100
Recall	100	100
Loss	0.0002	0.0315

According to the performance analysis displayed in Figure 4, the model achieved 100% accuracy, precision, and recall during training, with a low loss value of 0.0002. These high scores reflect the model's strong capability to accurately learn the features of breast cancer cases within the MIAS dataset. The model's consistently high performance during training shows it captured key patterns and achieved excellent accuracy.

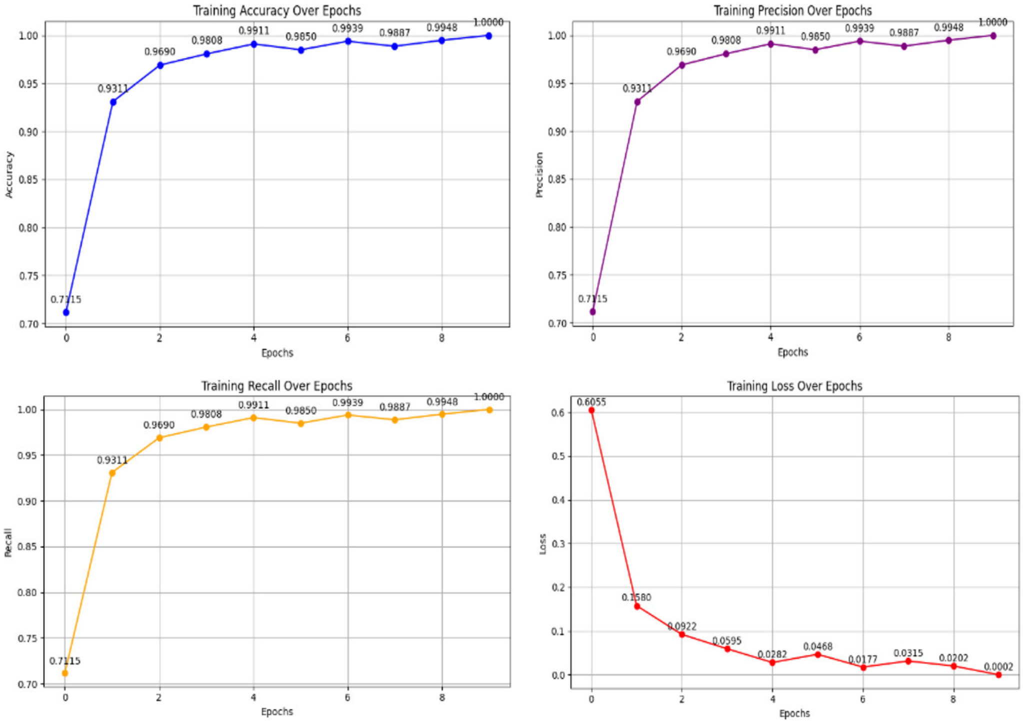

Fig. 4. Graphical line for performance analysis of MIAS training

Figure 5 showing testing performance. The model showed remarkable 100% accuracy, recall, and precision in classifying unknown data. The model's robust generalisation was confirmed by the testing loss of 0.0002, which was somewhat greater than the training loss but still showed minimal inaccuracy. The minimal 1.05% accuracy change between the training and testing phases, which demonstrates the model's high performance with low overfitting, further supports the model's efficacy in detecting patients with breast cancer in the MIAS dataset as seen in Table 8.

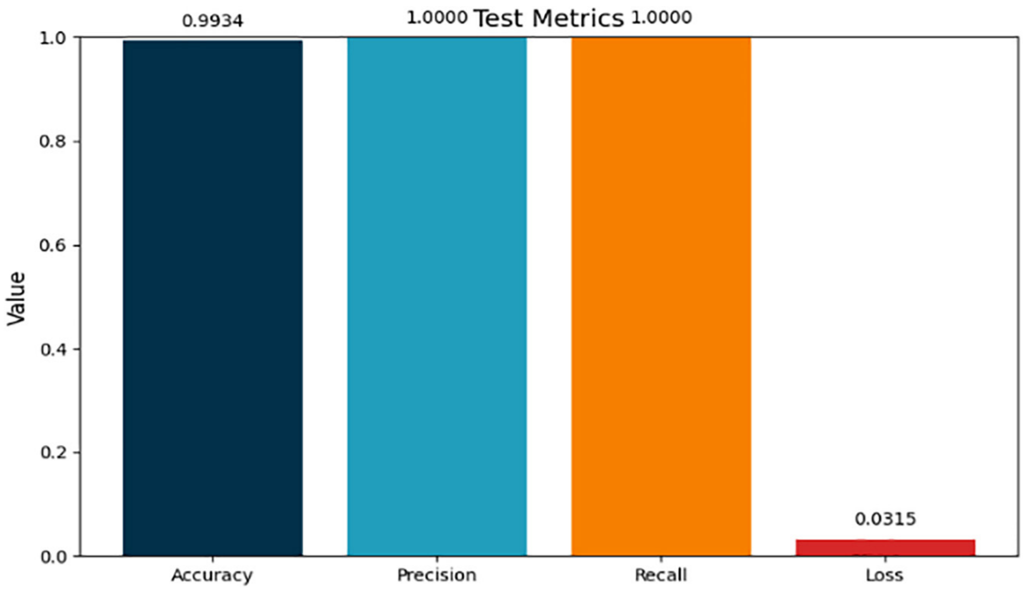

Fig. 5. Graphical bar for performance analysis of CBIS-DDSM testing

Table 8. Performance analysis comparison for MIAS training

Ref	Model	Accuracy	Precision	Recall	Loss
[10]	IMPACNN	98.32	–	–	–
[12]	PSOCNN	98.23	–	–	–
[11]	GWOCNN	97.98	97.76	–	–
	Proposed APOCNN	**99.34**	**100**	**100**	**0.0315**

The APO-optimised ConvNeXtBase model showed exceptional resilience and efficiency, achieving 99.34% accuracy, precision, and recall on the MIAS dataset with a low loss of 0.0315. On the other hand, a CNN model that was built on VGG16 and used transfer learning successfully gathered features without the need for further hyperparameter modifications, with an accuracy of 98.96%. A simpler CNN model that incorporated mammography and ultrasound data reached 96.55% accuracy, despite limitations imposed by its basic form. A (MA-CNN) showed high sensitivity but somewhat lower accuracy, with 96.47% accuracy, 96% sensitivity, and an AUC of 0.99. While a customised CNN without metaheuristic optimisation achieved 99.17% accuracy, a simple CNN achieved 97.9% accuracy. However, the APO-optimised model outperformed in terms of memory efficiency, loss, and accuracy, indicating its greater effectiveness for MIAS dataset classification.

4 CONCLUSION AND FUTURE WORK

This paper presents a DL-based CAD technique for classifying breast cancer using mammographic images from the CBIS and MIAS datasets. The system enhances the hyperparameters of the ResNet-50 and ConvNeXtBase models using the APO methodology. The model achieved an accuracy of 98.46%, with precision and recall also at 98.46%, and a low testing loss of 0.0574 when tested on the CBIS dataset. The MIAS dataset demonstrated an impressive accuracy of 99.34%, achieving perfect precision and recall at 100%, alongside a loss of 0.0315. The results highlight the model's robustness and effectiveness in classifying breast cancer. Future studies could witness progress in the generalisation of cancer detection by utilising APO-based CNN for ultrasound, MRI, and histology. Grad-CAM and SHAP, which boost AI interpretability, help build therapeutic trust by offering visual representations of decision-making. Additional data will validate the model. APO-optimised models give real-time CAD systems a precise classification. The implementation of these technologies has the potential to enhance the diagnostic capabilities of radiologists, streamline their workload, and facilitate early detection in clinical environments that are remote or lacking in resources. Lightweight or easily transportable devices for breast cancer screening can be designed.

5 REFERENCES

[1] K. E. Lukong, "Understanding breast cancer – The long and winding road," *BBA Clinical*, vol. 7, pp. 64–77, 2017. https://doi.org/10.1016/j.bbacli.2017.01.001

[2] American Cancer Society, "About breast cancer in men: What is breast cancer in men?" pp. 1–15, 2025. [Online]. https://www.cancer.org/cancer/types/breast-cancer-in-men/about/what-is-breast-cancer-in-men.html

[3] World Health Organization, "WHO guidelines for breast cancer screening," 2024. [Online]. Available: https://www.who.int/publications/i/item/9789241507936

[4] M. Farman, N. Gokbulut, E. Hincal, and K. S. Nisar, "Stability and BI-RADS 4 subcategories mitigate on cancer risk dynamics with fractional operators: A case study analysis," *Alexandria Engineering Journal*, vol. 109, pp. 41–57, 2024. https://doi.org/10.1016/j.aej.2024.08.065

[5] Centers for Disease Control and Prevention (CDC), "Facts about mammograms," 2024. [Online]. Available: https://www.cdc.gov/radiation-health/data-research/facts-stats/mammograms.html

[6] A. Ahmad, M. O. Kulachi, M. Farman, M. U. D. Junjua, M. B. Riaz, and S. Riaz, "Mathematical modeling and control of lung cancer with IL2 cytokine and anti-PD-L1 inhibitor effects for low immune individuals," *PLoS ONE*, vol. 19, no. 3, 2024. https://doi.org/10.1371/journal.pone.0299560

[7] American Cancer Society, "Breast density and your mammogram report," 2024. [Online]. Available: https://www.cancer.org/cancer/types/breast-cancer/screening-tests-and-early-detection/mammograms/breast-density-and-your-mammogram-report.html

[8] K. S. Nisar, M. O. Kulachi, A. Ahmad, M. Farman, M. Saqib, and M. U. Saleem, "Fractional order cancer model infection in human with CD8+ T cells and anti-PD-L1 therapy: Simulations and control strategy," *Sci. Rep.*, vol. 14, 2024. https://doi.org/10.1038/s41598-024-66593-x

[9] Y. LeCun *et al.*, "Backpropagation applied to handwritten zip code recognition," *Neural Computation*, vol. 1, no. 4, pp. 541–551, 1989. https://doi.org/10.1162/neco.1989.1.4.541

[10] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in *2017 International Conference on Engineering and Technology (ICET)*, Antalya, Turkey, 2017, pp. 1–6. https://doi.org/10.1109/ICEngTechnol.2017.8308186

[11] F. E. Fernandes Jr. and G. G. Yen, "Particle swarm optimization of deep neural networks architectures for image classification," *Swarm and Evolutionary Computation*, vol. 49, pp. 62–74, 2019. https://doi.org/10.1016/j.swevo.2019.05.010

[12] F. Azour and A. Boukerche, "An efficient transfer and ensemble learning based computer aided breast abnormality diagnosis system," *IEEE Access*, vol. 11, pp. 21199–21209, 2023. https://doi.org/10.1109/ACCESS.2022.3192857

[13] D. A. Ragab, O. Attallah, M. Sharkas, J. Ren, and S. Marshall, "A framework for breast cancer classification using Multi-DCNNs," *Computers in Biology and Medicine*, vol. 131, p. 104245, 2021. https://doi.org/10.1016/j.compbiomed.2021.104245

[14] A. Saber, M. Sakr, O. M. Abo-Seida, A. Keshk, and H. Chen, "A novel deep-learning model for automatic detection and classification of breast cancer using the transfer-learning technique," *IEEE Access*, vol. 9, pp. 71194–71209, 2021. https://doi.org/10.1109/ACCESS.2021.3079204

[15] D. Muduli, R. Dash, and B. Majhi, "Automated diagnosis of breast cancer using multi-modal datasets: A deep convolution neural network based approach," *Biomedical Signal Processing and Control*, vol. 71, 2022. https://doi.org/10.1016/j.bspc.2021.102825

[16] S. A. Agnes *et al.*, "Classification of mammogram images using multiscale all convolutional neural network (MA-CNN)," *J. Med. Syst*. vol. 44, no. 30, 2020. https://doi.org/10.1007/s10916-019-1494-z

[17] R. Sathesh Raaj, "Breast cancer detection and diagnosis using hybrid deep learning architecture," *Biomedical Signal Processing and Control*, vol. 82, p. 104558, 2023. https://doi.org/10.1016/j.bspc.2022.104558

[18] E. H. Houssein, M. M. Emam, and A. A. Ali, "An optimized deep learning architecture for breast cancer diagnosis based on improved marine predators algorithm," *Neural Comput. and Applic.*, vol. 34, pp. 18015–18033, 2022. https://doi.org/10.1007/s00521-022-07445-5

[19] K. Alnowaiser, A. Saber, E. Hassan, and W. A. Awad, "An optimized model based on adaptive convolutional neural network and grey wolf algorithm for breast cancer diagnosis," *PLoS ONE*, vol. 19, no. 8, 2024. https://doi.org/10.1371/journal.pone.0304868

[20] K. Aguerchi, Y. Jabrane, M. Habba, and A. H. el Hassani, "A CNN hyperparameters optimization based on particle swarm optimization for mammography breast cancer classification," *J. Imaging*, vol. 10, no. 2, p. 30, 2024. https://doi.org/10.3390/jimaging10020030

[21] C. B. Gonçalves, J. R. Souza, and H. Fernandes, "CNN architecture optimization using bio-inspired algorithms for breast cancer detection in infrared images," *Computers in Biology and Medicine*, vol. 142, p. 105205, 2022. https://doi.org/10.1016/j.compbiomed.2021.105205

[22] M. Dirik, S. Üniversitesi, and M. Gül, "Tuning artificial neural networks using particle swarm optimization algorithms for breast cancer diagnosis and prognosis," ResearchGate, 2024. [Online]. Available: https://www.researchgate.net/publication/379078002

[23] "MIAS database: The mammographic image analysis society database," [Online]. Available: https://datasetsearch.research.google.com/search?query=MIAS&docid=L2cvMTFrcXExbjAzbA%3D%3D

[24] J. Suckling *et al.*, "Mammographic Image Analysis Society (MIAS) database v1.21," Apollo – University of Cambridge Repository, 2015. https://doi.org/10.17863/CAM.105113

[25] "DDSM database: Digital database for screening mammography DDSM," [Online]. Available: https://www.mammoimage.org/databases/. [Accessed: May 18, 2025].

[26] "CBIS-DDSM Overview," [Online]. Available: https://www.cancerimagingarchive.net/collection/cbis-ddsm/

[27] Complex Adaptive Systems Laboratory, "CBIS-DDSM: Curated breast imaging subset of DDSM," 2018. [Online]. Available: https://complexity.cecs.ucf.edu/cbis-ddsm/. [Accessed: May 18, 2025].

[28] R. Sawyer-Lee, F. Gimenez, A. Hoogi, and D. Rubin, "Curated breast imaging subset of DDSM," *The Cancer Imaging Archive*, 2016. [Online]. Available: https://www.cancerimagingarchive.net/collection/cbis-ddsm/. [Accessed: May 18, 2025].

[29] Z. Hussain, F. Gimenez, D. Yi, and D. Rubin, "Differential data augmentation techniques for medical imaging classification tasks," *AMIA Annu Symp Proc.*, vol. 2017, pp. 979–984, 2018. PMID: 29854165; PMCID: PMC5977656.

[30] M. A. Obaid and W. M. Jasim, "Pre-convoluted neural networks for fashion classification," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 2, pp. 750–758, 2021. https://doi.org/10.11591/eei.v10i2.2750

[31] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson, "How transferable are features in deep neural networks?" *arXiv preprint arXiv:1411.1792*, 2014. [Online]. Available: https://arxiv.org/abs/1411.1792

[32] A. A. Nafea, M. S. Ibrahim, M. M. Shwaysh, K. Abdul-Kadhim, H. R. Almamoori, and M. M. AL-Ani, "A deep learning algorithm for lung cancer detection using EfficientNet-B3," *Wasit Journal of Computer and Mathematics Science (WJCMS)*, vol. 2, no. 4, pp. 68–76, 2023. https://doi.org/10.31185/wjcms.209

[33] Z. Liu, H. Mao, C.-Y. Wu, C. Feichtenhofer, T. Darrell, and S. Xie, "A ConvNet for the 2020s," *arXiv preprint arXiv:2201.03545*, 2022. [Online]. Available: http://arxiv.org/abs/2201.03545

[34] W. C. Wang, W. C. Tian, D. M. Xu, and H. F. Zang, "Arctic puffin optimization: A bio-inspired metaheuristic algorithm for solving engineering design optimization," *Advances in Engineering Software*, vol. 195, p. 103694, 2024. https://doi.org/10.1016/j.advengsoft.2024.103694

[35] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing & Management*, vol. 45, no. 4, pp. 427–437, 2009. https://doi.org/10.1016/j.ipm.2009.03.002

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