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Breast Cancer Classification through Meta-Learning Ensemble Model based on Deep Neural Networks

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Abstract

Predicting the development of cancer has always been a serious challenge for scientists and medical professionals. The prompt identification and prognosis of a disease is greatly aided by early-stage detection. Researchers have proposed a number of different strategies for early cancer detection. The purpose of this research is to use meta-learning techniques and several different kinds of convolutional-neural-networks(CNN) to create a model that can accurately and quickly categorize breast cancer(BC). There are many different kinds of breast lesions represented in the Breast Ultrasound Images (BUSI) dataset. It is essential for the early diagnosis and treatment of BC to determine if these tumors are benign or malignant. Several cutting-edge methods were included in this study to create the proposed model. These methods included meta-learning ensemble methodology, transfer-learning, and data-augmentation. With the help of meta-learning, the model will be able to swiftly learn from novel data sets. The feature extraction capability of the model can be improved with the help of pre-trained models through a process called transfer learning. In order to have a larger and more varied dataset, we will use data augmentation techniques to produce new training images. The classification accuracy of the model can be enhanced by using meta-ensemble learning techniques to aggregate the results of several CNNs. Ensemble-learning(EL) will be utilized to aggregate the results of various CNN, and a meta-learning strategy will be applied to optimize the learning process. The evaluation results further demonstrate the model's efficacy and precision. Finally, the suggested model's accuracy, precision, recall, and F1-score will be contrasted to those of conventional methods and other current systems.

Keywords: Deep-Learning; Meta-Learning, EL, CNN, Breast-Cancer, Classification

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Introduction

Carcinoma of the breast is a primary origin of demise in women throughout. Cancer of the breast first develops in the breast tissue and then spreads to other organs in the body. Not catching BC in its earliest stages increases the risk of death. The World-Health-Organization estimates that in 2021, 2.3M women across the universe will be diagnosed with BC. Early indications of breast cancer include breast lumps, thickness, and changes in breast shape, redness, and abnormal-discharge from the nipple. Risk factors for developing BC include age, gender, obesity, alcohol consumption, smoking, a personal or family history of the disease, radiation exposure, reproductive history (menarche, first pregnancy, menopause), and other factors (Nemade et al., 2023). Breast cancer treatment can be more successful if the disease is diagnosed at an earlier stage. The survival rate of a patient increases when a disease is detected early and treated with a amalgamation of surgical elimination, radiationtherapy, and medicines. This method of treating cancer can prevent the disease from progressing and spreading, reducing the likelihood of mortality from the illness (Rana et al., 2023).

Both invasive-ductal-carcinoma(IDC) and ductal-carcinoma-in-situ(DCIS) are among the most familiar types of BC; however, DCIS takes longer to develop and has less of an effect on patients' daily life, as illustrated in figure 1. IDC is found in as much as 50% to 70% of breast cancer cases. The IDC form is more deadly than the DCIS form, which accounts for just 20% of cases, because it affects all of the breast tissue. About 80% of people with breast cancer fall into this category. When all other cancers are taken into account, breast cancer is the primary origin of disability-adjusted years of life lost in female patients (Jabeen et al., 2022).

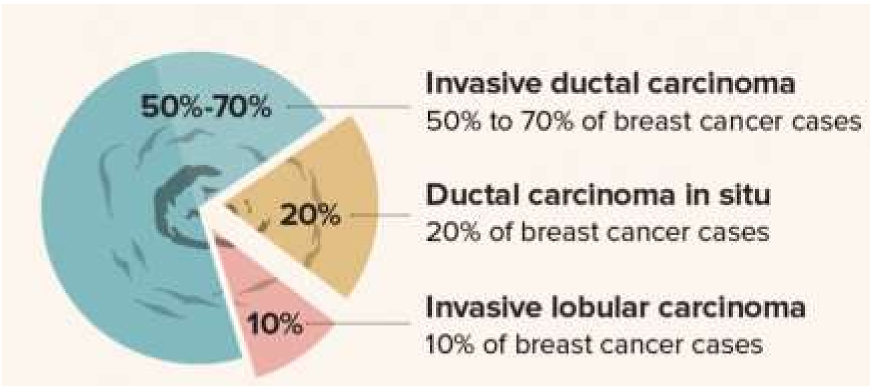

Figure 1. Types of Breast Cancers

Any woman, anywhere in the world, after reaching puberty, is at risk for developing breast cancer. The danger, however, grows with age. Life expectancy began to increase in the 1980s in countries that implemented early detection programs and various treatment options to remove invasive diseases. Breast cancer, unlike other forms of cancer, is not spread through casual contact. There are no known infectious causes of breast cancer, in contrast to cervical cancer caused by the human papillomavirus (HPV). Women over the age of 40 make up over half of all breast cancer cases, and these women have no other risk factors for the disease other being female (Lokesh et al., 2022). Family history, heavy alcohol use, and the use of hormone therapy after menopause are all risk factors that increase the likelihood that a woman may get breast cancer. A painless lump or thickening of the breast are common signs of breast cancer. If a woman feels a lump in her breast, no matter how painful it may be, she should consult a doctor right away. The vast majority of breast lumps are completely harmless. There is a 90% probability that a breast lump is completely harmless. Infections and benign tumors like fibroadenomas and cysts are examples of breast abnormalities that are not malignant. A complete medical checkup is necessary (Jakhar et al., 2023).

Tumor malignancy can be determined through imaging of the breast or, in some cases, through surgical removal of a tissue sample. Women with chronic anomalies (usually lasting more than one month) should undergo diagnostic procedures such breast imaging and tissue sampling (biopsy). There have been many developments in the use of machine-learning(ML) strategies for the diagnosis and classification of BC during the past few decades. These strategies consist of three stages: preprocessing, feature extraction, and classification. Preprocessing the mammography films to enhance the visibility of the images' periphery and intensity distributions allows for better interpretation and analysis. Many strategies have been described, and some of them work fairly well (Das et al., 2022). Machine learning is becoming increasingly popular, and it is likely that it will be offered to the public as a paid service in the near future. However, machine learning is still a challenging topic that typically requires the application of expert-level knowledge and abilities. A wide variety of knowledge and experience, including preprocessing, feature engineering, and classification strategies, is required to develop a trustworthy machine learning system (Yadala et al., 2023).

If diagnosed and treated early, breast cancer has a good chance of being successfully managed. Therefore, it is crucial that effective screening methods be easily accessible in order to diagnose breast cancer at an early stage. Imaging techniques including as mammography, ultrasonography, and thermography are frequently used in screening and diagnosing this condition. There is flexibility in the use of imaging techniques. However, mammography is expensive and is not the only method for detecting breast cancer early. Since mammography is completely ineffective for women who have hard breasts, diagnostic ultrasound techniques are gaining popularity as an alternative to mammography. Thermography may be more effective than ultrasonography at detecting small malignant tumors, yet neither method requires the use of radiation from X-rays (Pathan et al., 2022).

Twelve percent of American women will be spotted with invasive BC throughout their lifetimes, and the majority of these instances will have IDC. Anyone can get IDC, although older women are disproportionately affected. Almost two-thirds of women aged 55 and up have invasive breast cancer, according to the American Cancer Society. Thus, early diagnosis of tumor kind is essential. Tumors can be confirmed with a biopsy of the affected organ. Tissue type can be identified in a number of diverse ways. Machine learning-based technologies enhance medical decision support, allowing oncologists to deal with cancer more efficiently and affordably. Utilizing clinical data, a prediction system can be developed utilizing computer-aided automated diagnosis software to notice BC at timely. In comparison to alternative surgical procedures, unneeded harsh therapies, and expensive treatment costs, this method of diagnosis is more cost-effective, extremely safe, faster, and easier. In this research, we employ several deep learning strategies for tumor classification and evaluate their relative merits and weaknesses (Abhisheka et al., 2023). These methods aid in early cancer classification, which decreases the total amount of cases and boosts results for those already diagnosed with cancer. The following are the most significant findings from this study.

- Creating a meta-learning approach combined with a deep-learning(DL) strategy for improved BC recognition and early diagnosis;
- This study argued that meta-learning algorithms are optimized for few-shot learning, where objective is to acquire expertise in a novel task with minimal exposure to previous examples.
- In order to learn a new task efficiently, traditional machine learning algorithms often require a large amount of data. In order to accurately identify various metastases in breast cancers, it is proposed to construct a powerful ensemble classifier using a meta-learning method;
- The BUSI dataset was used for the demonstrations of the investigational results.

This article will be organized as pursues: Parts 1 and 2 give some context for the significance of early breast cancer detection. The proposed meta-learning system for BC diagnosis is presented in Section 3. The articles are wrapped up in Section 4, which discusses the outcomes of the proposed methodology.

Literature Review

Given that BC is the most common cancer among females worldwide, finding it at an early stage is essential for enhancing survival rates. Breast cancers in mammography and histopathology photos are being analyzed using DL strategies. Attention-based techniques, CNN, and multi-task learning are just a few of the approaches that have showed promise in this research. Data from a digitized Fine-Needle-Aspirate(FNA) has been analyzed and classified using a number of machine-learning techniques. Patients can utilize one of several prediction algorithms that have been published in the literature to help them spot breast cancer. Accuracy in detecting cancerous breast cells is used as a performance metric for the model. CNN is more precise than MLP. Using the WDBC dataset, achieved good results for diagnosing breast cancer. In order to automatically learn features from images for breast cancer classification, recommended a unified-DL architecture composed. In addition, many studies analyzed mammograms for breast cancer screening by employing CNN (Madhavi et al., 2023).

Deep-CNN based strategy and integrating the retrieved features were the final steps in the multi-stage approach used for breast cancer detection. An immune-inspired semi-supervised approach was developed for breast cancer diagnosis utilizing datasets from the UCI ML-repository. BC prognosis anticipation utilizing multidimensional data was proposed (Kumar et al., 2023). This model demonstrates how multidimensional models can outperform their one-dimensional counterparts and similar methods. A BC management system based on a DT

&NN was proposed. A unique voting-CDNN, was proposed and dataset has been subjected to several normalization and feature selection procedures. The authors claim that the model's results provide an average diagnosis accuracy of 100% (Pacal et al., 2022).

In order to classify mammography images used an LSTM-based CNN-based semantic features technique. In this work, we appraised the efficacy of the suggested model by measuring its classification accuracy and loss rate. Additional tree ensemble techniques are used to hybridize CNN and LSTM (Oloveira et al., 2023). Different convolution neural network–based breast cancer detection models were defined. The term "dropout" is defined in the context of using dropout to enhance NNs. Over-fitting is a common issue in machine learning systems, and dropout is a method for fixing it. In (Kumar et al., 2022), authors proposed a DL-optimized BC anticipation strategy. For the purpose of diagnosing BC, the authors have provided a deep recurrent-neural-network(DRNN) model trained with the Keras-Tuner Optimization method. An input-layer, five hidden-layers &dropout layers, and an output-layer make up the optimized deep RNN model. The BC dataset was used for this study (Iqbal et al., 2022). When it comes to classification, Softmax regression relies on the representation provided by the final stacked autoencoder layer. A model's actual accuracy is 98.60%. By examining many risk indicators related to breast cancer, the naive Bayes classifier has successfully classified patients into high-risk and low-risk categories. They have combined the boosting technique with an RBF neural network. On the UCI medical datasets WBC and WBCD, the proposed RBFNN techniques have been tested. Ten-fold cross-validation shows that both datasets have an accuracy of 97.4% (Himavarnika et al., 2023).

The CNN model successfully distinguished between breast cancers that were malignant and those that were benign in (Zahoor et al., 2022). They suggest using hidden Markov models (HMMs) to estimate the direction that pedestrians are moving in smart-cities. The results of many HMM-based strategies are compared. When compared to more conventional machine learning techniques, this one proved superior at predicting which way people were going when they were walking. Critical factors that contribute to strider walking track estimate were also determined in the study. If applied in real-time pedestrian-monitoring-systems in smart-cities, the proposed technology has the potential to greatly increase pedestrian safety in congested urban settings.

They improved prediction accuracy by combining DL models with feature selection and extraction strategies in (Nomani et al., 2022). In terms of predictive accuracy, this method far outperforms more conventional machine learning approaches. The study also indicated that the most important features of breast cancer were substantially associated with the disease's clinical outcome. This finding paves the way for additional investigation into developing robust prediction models for clinical outcomes in breast cancer. They talked about how deep learning can be used in conjunction with mammography to improve cancer detection and classification accuracy compared to standard approaches. They also stressed the value of TL and data-augmentation strategies for enhancing design performance, as well as the need for bigger datasets when training DL-strategies (Chillakuru et al., 2023). They also talked about how advanced knowledge of breast histology can be used to examine tissue architectures and spot cancer-related trends. The model uses a CNN to focus on the best features for classification. We put the proposed model through its paces on a public dataset and discovered that it outperformed both conventional ML &DL strategies. By focusing on the most important parts of mammogram images, the suggested methodology can cut down on false positives and wasteful biopsies (Sucharitha et al., 2023). Researchers wanted to enhance the precision of a BC-diagnosis through the use of automated image processing. To train and test their algorithm, the academicians divided a freely accessible dataset of breast-histopathology photos into two distinct groups. Next, they used the CNN with small SE blocks to train and assess the model's performance on identifying cancerous and non-cancerous tissue in photos. The proposed model had a better area under the curve (AUC) than several other cutting-edge deep learning models (Latha et al., 2023). They demonstrate that their multi-task learning strategy improves classification accuracy over that of single-task learning methods. They predict that this method could be useful in other categorization tasks involving medical images. Their study introduces a deep residual network–based strategy for categorizing breast cancer. They stress the value of precise breast cancer identification through mammography for early detection and therapy (Patra et al., 2022).

Using a deep learning strategy, in particular residual networks, they are able to extract information and classify images. A large dataset of mammography images is utilized to train and estimate the proposed approach. The results validate the efficacy of the suggested system and demonstrate that it provides significant improvements over prior approaches to breast cancer classification. This study contributes to ongoing efforts to advance breast cancer diagnosis. Using a multi-model approach, the authors (Kumar et al., 2023) propose a DL-approach for categorizing BC. The researchers employed TL to modify pre-trained for the BC dataset and combine many models in order to enhance classification exactness. The results illustrate that the proposed strategy performs better than current DL-strategies for classifying BC. The BC-diagnosis work uses DL-methods, which can be applied to improve diagnostic exactness in clinical settings. The ideal weight initialization for various CNN models can be learned with the help of the method proposed in (Cui et al., 2023), which makes use of a meta-learning framework. The CNN models have already been trained on other datasets to recognize a wide variety of characteristics. This method of transfer learning works well, even with small datasets. The meta-learning strategy is used to combine the necessary learners in the suggested research. Overfitting is a common problem that has been noted in many previous researches and is the primary focus of the current literature review. Our research was designed to help fix these widespread issues.

Methodology

Breast cancer survival rates can be greatly grown via proactive screening and early diagnosis. Recently, a meta-learning technique for BC-classification employing multiple-CNNs has demonstrated promising outcomes in automatic-classification of BC using DL-based CAD systems. We used the Breast-Ultrasound-Imaging-Dataset(BUSI) to evaluate how well our proposed method performed. Breast ultrasound images in the BUSI dataset include a wide range of features, making them challenging to categorize as either benign/malignant. The diagnostic accuracy and reliability for breast cancer are both enhanced by the proposed technique.

Proposed Methodology

In this division, we describe in depth the method presented for categorizing breast cancer. In Figure 2, we see a high-level summary of the proposed strategy for initially categorizing breast cancer. Pre-processing improves the breast cancer photos in terms of resolution, contrast, and removal of unwanted noise. After the photos have been analyzed, some elementary CNN models trained on the ImageNet dataset are used to extract deep learning properties. The final breast cancer picture categorization is handled by a meta-learner, which is fed anticipation outcomes from the baseline CNN-design. In order to train both the basic classifier and the meta-learner, the BUSI-dataset, which includes both benign &malignant BC-images, has been used. The meta-model is utilized to identify unseen BC photos as benign/malignant. It was trained on the BUSI-dataset, which includes both benign &malignant BC-scans.

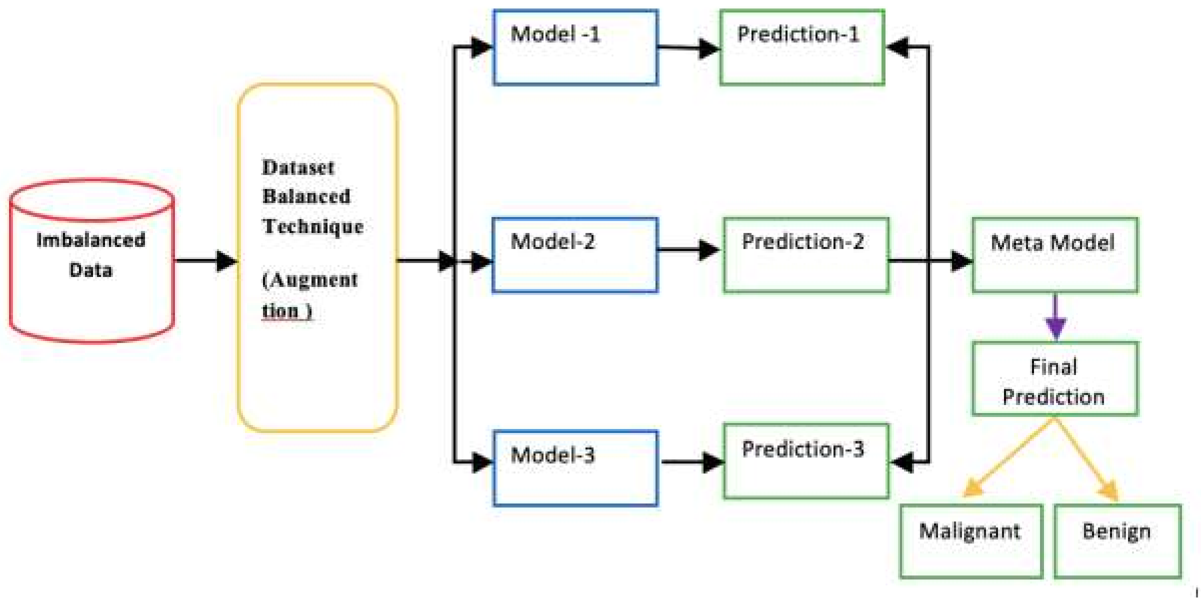

Figure 2. Concept diagram of the proposed model

Dataset

The Breast Ultrasound Images Dataset (BUSI) has been used; it is divided into two groups: benign and alignant. The two groups are extremely unbalanced. An unbalanced dataset can have a devastating effect on the accuracy of a classification model. Classification bias manifests are seen in deep networks, when they are trained on an uneven dataset (Ashreetha et al., 2022). Both classes were also made larger through the use of data augmentation. Malignant and benign breast cancer photos totaling 10,000 are included in the new collection. There are 10,000 total photos in the database, with 5,000 in the benign category and 10,000 in the malignant one. Annotations such as tumor location and size are included for each image in the dataset. Computer-aided-diagnosis (CAD) systems, which use ML & DL strategies to assist radiologists in interpreting medicinal images, have found the BUSI-dataset to be particularly useful in their development and evaluation (Rao et al., 2023). Researchers and medical professionals interested in BC identification and diagnosis will find the BUSI dataset to be an invaluable tool. By training and evaluating ML-strategies on this dataset, researchers can improve the precision and velocity of future CAD systems. Based on the biopsy findings, the images were labeled as benign or malignant. Seventy percent, ten percent, and twenty percent of the photos, respectively, were distributed among the training, validation, and test sets (Suneel et al., 2024).

Pre-Processing

Research into BC-classification utilizing meta-learning methods and multiple-CNNs is discussed. The goal of this meta-learning technique is to enhance CNN performance by training multiple-CNNs on BUSI and then merging their anticipations. The images of breast cancer tumors from the BreaKHis collection were used. This open dataset features segregation into three distinct phases: training, validation, and testing. 70% of the images will be utilized for train, 10% for verification, and 20% for evaluation (Deivasigamani et al., 2023). Before implementing the meta-learning strategy, the process involves training a large number of CNNs on individual segments of the training dataset. The learning-rate, batch-size, and optimizer are only a few of the hyperparameters shown for each CNN. The weighted average of predictions made by the trained CNNs is then applied to the testing dataset. The effectiveness of the proposed method was measured across a wide range of indicators, such as precision, responsiveness, and specificity. The outcomes show that the proposed strategy is more accurate than many baseline models for classifying breast cancer. They enhance CNN performance for BC-classification and can be used to other medicinal imaging activities where accurate predictions are needed (Chanchal et al., 2023).

Classification and Fine-Tuning

In this research, several distinct CNNs were used as the foundational models for the meta-learning approach taken. These models were first trained on the large ImageNet dataset, which includes many different general picture datasets. They were then fine-tuned with the use of the breast ultrasound dataset. The following CNN base architectures were employed in this study.

InceptionV3

With the use of factorized convolutions, the number of parameters in InceptionV3, a deep CNN architecture, is greatly reduced. Inception uses deep convolutional neural networks as the basis for an image classification framework. Since its initial presentation in 2014, its use as a tool for image recognition has skyrocketed (Ahmed et al., 2021). The Inception model employed in this research was pre-trained using the publicly available and widely-used ImageNet dataset. This dataset includes millions of images and serves as a standard for image recognition. We've included a dropout layer and seven-way softmax layer in the architecture as well as a dense-layer with "relu" activation to progress the model's capacity to be fine-tuned on the dataset. This layout is fine-tuned using a stochastic-gradient-descent(Adam) optimizer trained on 10,000 image samples over 30 iterations at a learning-rate of 0.0001 and a momentum of 0.9 (Muthapa et al., 2023).

ResNet50

ResNet50 is a deep convolutional neural network architecture that makes use of residual connections to help stop the vanishing gradient problem. The deep residual neural network architecture ResNet50 was developed in 2015. It's meant to include skip links that speed up the gradient's journey through the network. The ResNet50 model utilized in this research was trained using data from the ImageNet dataset Agrawal et al., 2023). We improved ResNet50 by adding a dense-layer with'relu' activation, as well as dropout and softmax layers with varying results. An Adam-optimizer with a momentum of 0.9 and a learning-rate of 0.0001 is utilized to fine-tune the enhanced ResNet50 on 10,000 photos over the course of 30 iterations.

DenseNet121

It is a deep-CNN architecture that prioritizes communication across layers through the use of dense connections. In 2016, the DenseNet 121 deep convolutional neural network architecture was introduced. Its goal is to improve gradient flow and cut down on network parameters by giving each layer direct access to the feature maps of the layers below it (Dash et al., 2022). Thus, we used denseNet 121 as a model after making certain alterations, such as adding a dense-layer with "relu" activation, dropout and softmax layers with varying outcomes. The modified architecture was then trained on a dataset of 10,000 photos over the course of 30 iterations utilizing a learning-rate of 0.0001 and a momentum of 0.9 for the Adam optimizer.

Feature Extraction

Classification and other analyses can benefit from feature extraction from raw data. In order to classify breast cancer from medical images, features extraction is crucial as it reveals the important characteristics of the images that hint to malignant tissue. Two methods utilized in breast cancer classification are manually designed feature extraction and deep learning feature extraction. An example of manual feature extraction is the extraction of features including texture, shape, and intensity depends on prior-knowledge of malignant &benign tissue parameters (Muduli et al., 2023). A BC classifier is then trained using these features. In contrast, deep CNN is used in the context of DL-based feature extraction to automatically learn pertinent medical images. Due to its ability to discover intricate patterns and connections in data that human-created features may miss, this method has shown encouraging results in breast cancer categorization.

Meta-Learning

The goal of meta-learning methods is to train a meta-model that can anticpate how well other approaches will do on a given task. In most cases, the meta-model is trained with data describing the model's own attributes, such as its complexity, precision, and generalizability. In order to provide an accurate prediction of the test set's final classification, meta-models were trained using the results of the 3-basic types of anticipations on the test set. Our findings demonstrate that this allowed us to boost our meta-model's prediction accuracy.

Figure 3 shows how our proposed methodology ensembles three unique CNN architectures: ResNet50, DenseNet121, and InceptionV3. None of them used cutting-edge meta-learning to sort papers into benign and malignant categories. The model's learning rate can be adjusted with the help of an optimizer. Adam is used as an optimizer in this study. The accuracy metric is used to evaluate the training accuracy score. Binary crossentropy is used to pinpoint the damage. This loss function is widely used in the field of binary class classification. A lower loss score indicates greater model performance. The meta-learner receives the results from each model. For this purpose, we employ a meta-learner in the form of a logistic-regression classifier.

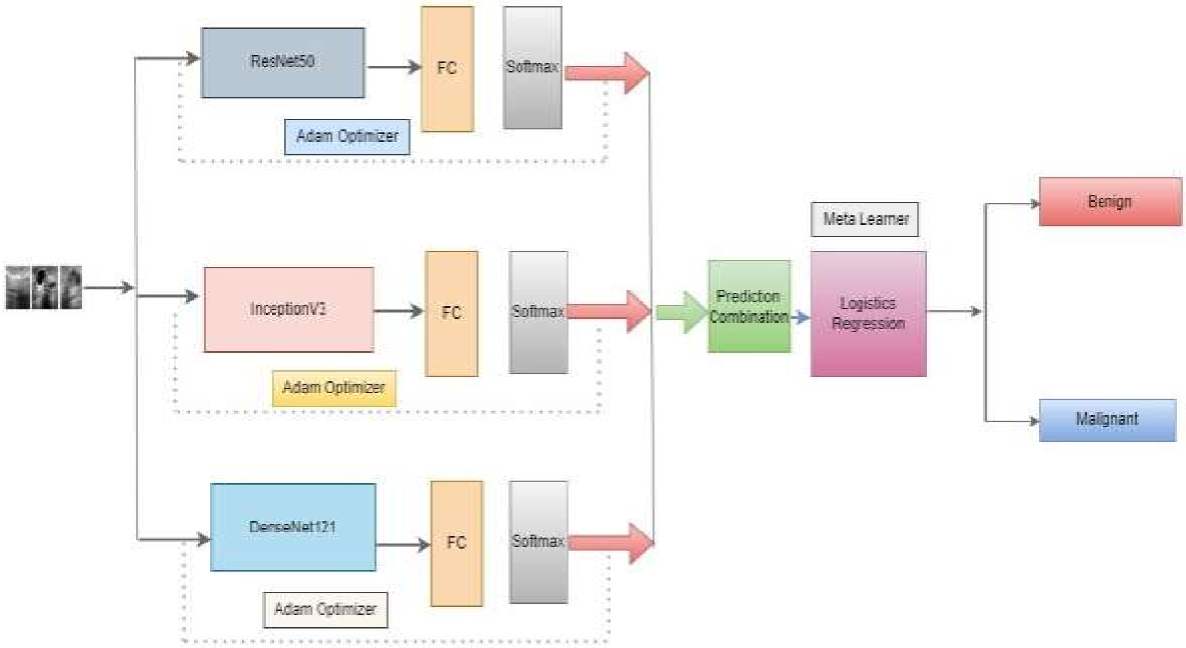

Figure 3. Proposed Model Architecture

Performance Metrics

In this research, we proposed a novel approach to BC classification using metalearning with multiple CNN as base models. Three popular CNN architectures (InceptionV3, ResNet50, &DenseNet 121) were employed as the basis for this recommended method. The results showed that the suggested technique has better accuracy (Acc), precision (Pe), recall (Re), specificity (Sp), and F1-score than the separate CNN models. The most impressive outcomes were from a meta-learning approach that included three foundational models above mentioned approaches. Using Eq. (1)-(5), the metrics can be calculated. According to the results, meta-learning with base approaches is an effective approach to breast cancer classification. The method allows for the advantages of multiple CNN models to be pooled together to achieve better results than any of them could achieve on their own. Overfitting is mitigated, and the model's ability to generalize is expanded, when numerous base models are used.

There are significant implications for improving classification accuracy and speed using the proposed strategy for breast cancer categorization. Researchers recommended employing a wider variety of CNN models as baselines in future research, as well as incorporating more forms of medical imagery and exploring further meta-learning approaches.

$$\text{Acc} = \frac{Tr_{Positive} + Tr_{Negative}}{Tr_{Positive} + Tr_{Negative} + Fa_{Positive} + Fa_{Negative}} \quad (1)$$

$$\text{Pe} = \frac{Tr_{Positive}}{Tr_{Positive} + Fa_{Negative}} \quad (2)$$

$$Sp = \frac{Tr_{Negative}}{Tr_{Negative} + Fa_{Negative}} \quad (3)$$

$$Re = \frac{Tr_{Positive}}{Tr_{Positive} + Fa_{Postive}} \quad (4)$$

$$\text{F1-score} = 2 \times \left(\frac{Pe \times Re}{Pe + Re}\right) \quad (5)$$

Results and Discussion

To prove our meta-ensemble strategy efficacy in detecting benign &malignant BC, we conduct a comprehensive evaluation and analysis of performance results acquired utilizing different model configurations. We will now move on to discussing the experimental setup, key performance metrics, and results (both quantitative and qualitative). The full dataset is divided into training, validation, and test sets using a 70:10:20 split ratio. Meta ensemble models and their constituent sub-models are trained and evaluated using the dataset's images with the aforementioned ratio. To combat the problem of a small dataset, enhance training efficiency, and prevent model overfitting, we employ picture augmentation. Image enhancement is also believed to increase model generalization. As a solution to the problem of a small training dataset, data augmentation was implemented.

Table 1 displays the results of using various CNN-approaches and the suggested meta-model to categorize BC-scans into benign (B) &malignant (M) categories. The accuracy with which each CNN model could distinguish between healthy and cancerous images was used as a criterion for their evaluation. F1-score, accuracy, precision, and recall were used to evaluate performance. When comparing benign and cancerous images, InceptionV3 achieves an accuracy of 0.83. Accuracy of 0.78 is achieved for noncancerous tissue and 0.91 for cancerous tissue, 0.9 for healthy pictures and 0.74 for cancerous ones. The F1 for healthy pictures is 0.85, while cancerous ones get 0.82.

Table 1. Performance assessment of the proposed models

Model	Category	Acc(%)	Pe(%)	Re(%)	F1(%)
InceptionV3	B	84	79	94	86
	M		91	75	83
ResNet50	B	89	85	93	91
	M		93	84	88
DenseNet121	B	85	82	88	86
	M		87	81	84
Proposed	B	92	89	96	92
	M		96	91	90

ResNet50's Acc for healthy and cancerous pictures is 0.88. Malignant tumors have a Pe of 0.93, while benign ones are 0.84. Re is 0.94 for noncancerous photos and Re 0.82 for cancerous ones. When comparing benign and malignant scans, the F1 for B was 0.89 and the M value was 0.88. For benign and malignant pictures, DenseNet121 achieves an accuracy of 0.84. Accuracy is achieved of 0.81 for noncancerous tissue and 0.88 for cancerous tissue. Recall 0.89 for healthy photos and 0.79 for cancerous ones. For benign photos, the model scored 0.85 on the F1 scale, but for malignant ones, it scored 0.83.

When compared to the separate CNN models, our suggested meta-model had better Acc, Pe, Re, and 1. The following are the outcomes of the metamodel. Overall, the model performed quite well when measured by accuracy scores, achieving a value of 0.92 for both B &M pictures. Pe scores ranged from 0.89 for healthy photos to 0.96 for cancerous ones. For healthy photos, recall was 0.96, whereas it was 0.91 for cancerous ones. Images classified as benign had an F1 score of 0.92, whereas those classified as malignant had a score of 0.90.

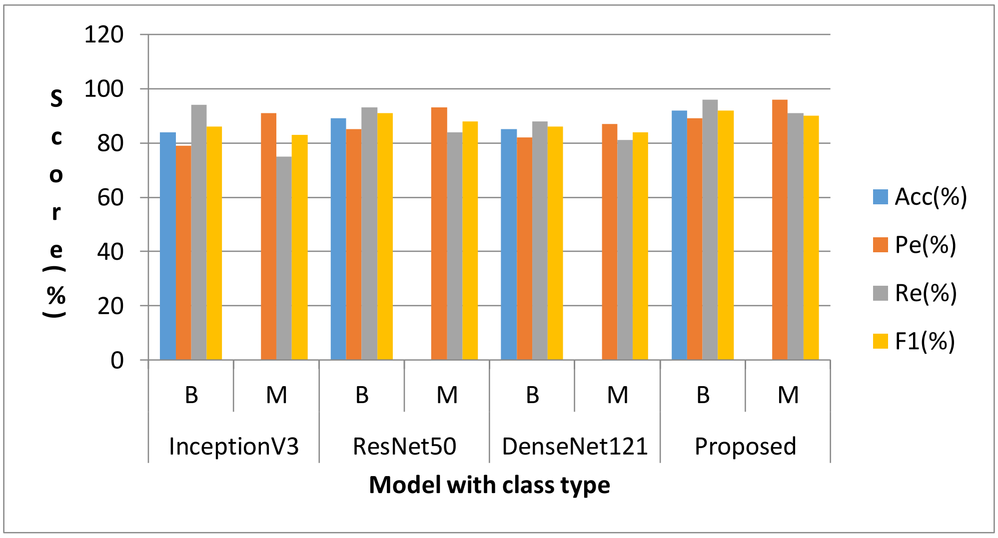

Figure 4. Performance comparison

Figure 4 displays a comparison of the results, suggesting that the proposed CNN may be an effective means of attractive the precision and dependability of BC diagnoses. It is essential for an effective diagnosis system to have accurate classification of cancer images across all categories. The meta-model performs admirably in differentiating benign cases from malignant moles. Good outcomes have also been attained through the use of data augmentation and dropout regularization.

Receiver-operating-characteristic(ROC) curves, as shown in Figure 5, are used to better grasp the class distinction in the researched meta-models. In a ROC curve, a range of threshold values is used to plot the true-positive-rate(TPR) against false-positive-rate(FPR) based on the probability outcomes of deep learning models. The True Positive Rate (TPR) represents the likelihood of correctly labeling healthy pictures as cancerous. On the other hand, false positive rates (FPR) highlight the danger of false alarms, or the possibility that a healthy image would be wrongly identified as having signs of cancer.

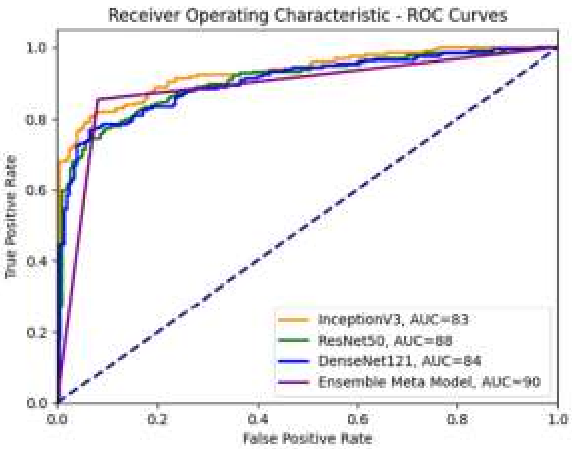

Figure 5. ROC curves for the DL-models

Conclusion

A unique method is discussed in this work for classifying breast cancer, and it is shown to have produced conventional results on the BUSI-dataset. The paper's method was able to attain 92% precision. Better generalization and higher accuracy were achieved by integrating multiple-CNN models into a meta-learning framework. This was especially true for the detection of malignant tumors. This research showed how meta-learning and ensemble approaches can be used to make a breast cancer diagnosis more precise and time-efficient. It is possible to apply the method developed for use with medical imaging datasets to other forms of cancer and other medical diseases. The researcher offered numerous suggestions for future research. One avenue to pursue would be to test out and evaluate the efficacy of alternative meta-learning algorithms to the one provided in the research, such as reinforcement learning. Clinical data like patient-history, might be incorporated into the classification model, and this could be explored as another avenue. Additionally, it was mentioned that the dataset employed in the study has several limitations, such as a small sample size and a lack of case variety. Using meta-learning and ensemble approaches, the suggested method for breast cancer classification has shown encouraging results on various medical imaging datasets. The complexity of a model can rise as a result of the many trainable parameters used in meta-learning. The future of reducing the amount of trainable factors while maintaining or boosting performance lies in the design of innovative architecture. The goal is to identify less complex structures that, with fewer settings, can adequately represent the underlying patterns in the data.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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References

Abhisheka, B.; Biswas, S. K. & Purkayastha, B. (2023). A comprehensive review on breast cancer detection, classification and segmentation using deep learning. *Archives of Computational Methods in Engineering*, 1-30.

Agrawal, A. (2023). Classification and Detection of Brain Tumors by Aquila Optimizer Hybrid Deep Learning Based Latent Features with Extreme Learner. In *ITM Web of Conferences* (53). EDP Sciences.

Ahmed, S. T.; Singh, D. K.; Basha, S. M.; Abouel Nasr, E.; Kamrani, A. K.; & Aboudaif, M. K. (2021). Neural network based mental depression identification and sentiments classification technique from speech signals: A COVID-19 Focused Pandemic Study. *Frontiers in public health*, *9*, 781827.

Ashreetha, B.; Devi, M. R.; Kumar, U. P.; Mani, M. K.; Sahu, D. N. & Reddy, P. C. S. (2022). Soft optimization techniques for automatic liver cancer detection in abdominal liver images. *International journal of health sciences*, *6*.

Chanchal, A. K.; Lal, S.; Barnwal, D.; Sinha, P.; Arvavasu, S. & Kini, J. (2023). Evolution of LiverNet 2. x: Architectures for automated liver cancer grade classification from H&E stained liver histopathological images. *Multimedia Tools and Applications*, 1-31.

Chillakuru, P.; Madiajagan, M.; Prashanth, K. V.; Ambala, S.; Shaker Reddy, P. C. & Pavan, J. (2023). Enhancing wind power monitoring through motion deblurring with modified GoogleNet algorithm. *Soft Computing*, 1-11.

Cui, C.; Yang, H.; Wang, Y.; Zhao, S.; Asad, Z.; Coburn, L. A. & Huo, Y. (2023). Deep multi-modal fusion of image and non-image data in disease diagnosis and prognosis: a review. *Progress in Biomedical Engineering*.

Das, A. & Mohanty, M. N. (2022). Design of ensemble recurrent model with stacked fuzzy ARTMAP for breast cancer detection. *Applied Computing and Informatics*.

Dash, P. B.; Behera, H. S. & Senapati, M. R. (2022). Breast Cancer Mammography Identification with Deep Convolutional Neural Network. In *Computational Intelligence in Data Mining: Proceedings of ICCIDM 2021* (pp. 741-752). Singapore: Springer Nature Singapore.

de Oliveira, C. I.; do Nascimento, M. Z.; Roberto, G. F.; Tosta, T. A.; Martins, A. S. & Neves, L. A. (2023). Hybrid models for classifying histological images: An association of deep features by transfer learning with ensemble classifier. *Multimedia Tools and Applications*, 1-24.

Deivasigamani, S.; Rani, A.J.M.; Natchadalingam, R.; Vijayakarthik, P.; Kumar, G.B.S. and Reddy, P.C.S. (2023), August. Crop Yield Prediction Using Deep Reinforcement Learning. In 2023 Second International Conference on Trends in Electrical, Electronics, and Computer Engineering (TEECCON) (pp. 137-142). IEEE.

Himavarnika, A. & Prasanthi, P. (2023). A Statistical Modelling to Detect Carcinoma Cancer in Its Incipient Stages in Healthcare. *Journal of Coastal Life Medicine*, *11*, 468-481.

Iqbal, M. S.; Ahmad, W.; Alizadehsani, R.; Hussain, S. & Rehman, R. (2022, November). Breast Cancer Dataset, Classification and Detection Using Deep Learning. In *Healthcare* (10) 12, 2395.

Jabeen, K.; Khan, M. A.; Alhaisoni, M.; Tariq, U.; Zhang, Y. D.; Hamza, A. & Damaševičius, R. (2022). Breast cancer classification from ultrasound images using probability-based optimal deep learning feature fusion. *Sensors*, *22*(3), 807.

Jakhar, A. K.; Gupta, A. & Singh, M. (2023). SELF: a stacked-based ensemble learning framework for breast cancer classification. *Evolutionary Intelligence*, 1-16.

Kumar, G. R.; Reddy, R. V.; Jayarathna, M.; Pughazendi, N.; Vidyullatha, S. & Reddy, P. C. S. (2023). Web application based Diabetes prediction using Machine Learning. In *2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)* pp. 1-7, IEEE.

Kumar, K.; Pande, S.V.; Kumar, T.; Saini, P.; Chaturvedi, A.; Reddy, P.C.S. & Shah, K.B. (2023). Intelligent controller design and fault prediction using machine learning model. *International Transactions on Electrical Energy Systems*, *2023*.

Kumar, S. S.; Ahmed, S. T.; Xin, Q.; Sandeep, S.; Madheswaran, M. & Basha, S. M. (2022). Unstructured Oncological Image Cluster Identification Using Improved Unsupervised Clustering Techniques. *Computers, Materials & Continua*, *72*(1).

Latha, S. B.; Dastagiraiah, C.; Kiran, A.; Asif, S.; Elangovan, D. & Reddy, P. C. S. (2023, August). An Adaptive Machine Learning model for Walmart sales prediction. In *2023 International Conference on Circuit Power and Computing Technologies (ICCPCT)* (pp. 988-992). IEEE.

LK, S. S.; Ahmed, S. T.; Anitha, K. & Pushpa, M. K. (2021, November). COVID-19 outbreak based coronary heart diseases (CHD) prediction using SVM and risk factor validation. In *2021 Innovations in Power and Advanced Computing Technologies (i-PACT)* (pp. 1-5). IEEE.

Lokesh, S.; Priya, A.; Sakhare, D. T.; Devi, R. M.; Sahu, D. N. & Reddy, P. C. S. (2022). CNN based deep learning methods for precise analysis of cardiac arrhythmias. *International journal of health sciences*, *6*.

Madhavi, G. B.; Bhavani, A. D.; Reddy, Y. S.; Kiran, A.; Chitra, N. T. & Reddy, P. C. S. (2023, June). Traffic Congestion Detection from Surveillance Videos using Deep Learning. In *2023 International Conference on Computer, Electronics & Electrical Engineering & their Applications (IC2E3)* pp. 1-5, IEEE.

Muduli, D.; Kumar, R. R.; Pradhan, J. & Kumar, A. (2023). An empirical evaluation of extreme learning machine uncertainty quantification for automated breast cancer detection. *Neural Computing and Applications*, 1-16.

Muthappa, K. A.; Nisha, A. S. A.; Shastri, R.; Avasthi, V. & Reddy, P. C. S. (2023). Design of high-speed, low-power non-volatile master slave flip flop (NVMSFF) for memory registers designs. *Applied Nanoscience*, 1-10.

Nemade, V.; Pathak, S. & Dubey, A. K. (2023). Deep learning-based ensemble model for classification of breast cancer. *Microsystem Technologies*, 1-15.

Nomani, A.; Ansari, Y.; Nasirpour, M. H.; Masoumian, A.; Pour, E. S. & Valizadeh, A. (2022). PSOWNNs-CNN: a computational radiology for breast cancer diagnosis improvement based on image processing using machine learning methods. *Computational Intelligence and Neuroscience*, *2022*.

PACAL, İ. (2022). Deep learning approaches for classification of breast cancer in ultrasound (US) images. *Journal of the Institute of Science and Technology*, *12*(4), 1917-1927.

Pathan, R. K.; Alam, F. I.; Yasmin, S.; Hamd, Z. Y.; Aljuaid, H.; Khandaker, M. U. & Lau, S. L. (2022, November). Breast Cancer Classification by Using Multi-Headed Convolutional Neural Network Modeling. In *Healthcare* p. 2367. MDPI.

Patra, A.; Behera, S. K.; Barpanda, N. K. & Sethy, P. K. (2022). Effect of Microscopy Magnification Towards Grading of Breast Invasive Carcinoma: An Experimental Analysis on Deep Learning and Traditional Machine Learning Methods. *Ingénierie des Systèmes d'Information*, *27*(4).

Rana, M. & Bhushan, M. (2023). Classifying breast cancer using transfer learning models based on histopathological images. *Neural Computing and Applications*, *35*(19), 14243-14257.

Rao, K. R.; Prasad, M. L.; Kumar, G. R.; Natchadalingam, R.; Hussain, M. M. & Reddy, P. C. S. (2023, August). Time-Series Cryptocurrency Forecasting Using Ensemble Deep Learning. In *2023 International Conference on Circuit Power and Computing Technologies (ICCPCT)* (pp. 1446-1451). IEEE.

Sucharitha, Y.; Reddy, P. C. S. & Chitti, T. N. (2023, July). Deep learning based framework for crop yield prediction. In *AIP Conference Proceedings* 1 (2548), AIP Publishing.

Suneel, S.; Balaram, A.; Amina Begum, M.; Umapathy, K.; Reddy, P. C. S. & Talasila, V. (2024). Quantum mesh neural network model in precise image diagnosing. *Optical and Quantum Electronics*, 56(4), 559.

Yadala, S.; Pundru, C. S. R. & Solanki, V. K. (2023, March). A Novel Private Encryption Model in IoT Under Cloud Computing Domain. In *The International Conference on Intelligent Systems & Networks* pp. 263-270. Singapore: Springer Nature Singapore.

Zahoor, S.; Shoaib, U. & Lali, I. U. (2022). Breast cancer mammograms classification using deep neural network and entropy-controlled whale optimization algorithm. *Diagnostics*, *12*(2), 557.

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