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Enhancing Breast Cancer Detection: A Novel Deep Learning Approach Using Hybrid Convolutional Neural Networks and Residual Number Systems

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Abstract

Introduction: The detection of breast cancer is vital for intervention and treatment as soon as possible. This study attempts to use a new hybrid deep learning approach that is a combination of Convolutional Neural Networks (CNNs) and Residual Number Systems (RNS) to more precisely detect cancer of the breasts.

Methods: INBREAST and MINI-DDSM datasets were employed to evaluate the hybrid model. Precision, recall, F1-score, and accuracy of these were employed to determine effects of the model compared to existing methods.

Results: The hybrid model was found to be 99% accurate in training using INBREAST dataset, and 91.5% in validation using INBREAST dataset, while MINI-DDSM dataset was found to be 98% in training and 95.02% in validation in terms of accuracy. The model was superior in MINI-DDSM dataset compared to existing models such as ZFNET and ResNet18 in precision, recall, and accuracy metrics. INBREAST dataset was hard to manage due to its nature of complexity, hence it was found to produce low precision and recall despite having high overall precision in performance.

Conclusion: This study highlights the potential of the proposed hybrid deep learning approach for breast cancer detection, especially in simpler datasets. Future research should focus on techniques such as data augmentation, transfer learning, and ensemble methods to improve robustness and generalizability across diverse imaging scenarios. The findings contribute to the integration of deep learning in medical diagnostics, aiming for more accurate and efficient breast cancer detection systems.

Keywords: Breast cancer detection, Deep learning, Convolutional neural networks, Residual number systems, Hybrid model

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Introduction

With multiple contributing causes, breast cancer is a major health concern, especially in Asia. A global partnership is required for early detection, better healthcare, and treatment of this disease since it places a heavy financial, psychological, and physical cost on individuals and society. Breast cancer is predicted to claim the lives of 300,590 new cases and 43,170 deaths in the US in 2023 (1). If breast cancer is detected in its early stages, before it grows significantly or spreads, the chances of successful treatment are much higher. The American Cancer Society reports a 5-year relative survival rate of 99% for localized early-stage breast cancer (2). The most accurate detection method in its initial phase is regular screening. Screening is a process of performing tests and examinations to diagnose disease in symptomless subjects. Early detection of cancer of breasts is done using regular use of a mammogram (2). Cancerous tumors metastasize to other parts of the body, and many cancer patients do not exhibit symptoms (3). Early detection of cancer is, hence, facilitated using regular cancer screening of breasts (3). There are various methods devised for accurate diagnosis of cancer of breasts. Screening of breasts, or also referred to as a mammography, is a method of cancer of breasts diagnosis. Consequently, accurate classification of benign tumors is essential to encourage patients to seek appropriate treatment and receive better care. Radiologists base their diagnoses on the morphological and boundary features of breast masses. The more irregular the shape of the mass, the higher the probability of malignancy. Overall, classification results depend on the findings of breast tissue segmentation, which is a time-consuming and labor-intensive task for radiologists. As a result, several machine learning (ML) and deep learning (DL) methods have been employed for medical predictions in the field of breast cancer to aid in accurate diagnosis(4-9).

This study presents experimental comparative studies to evaluate the performance of the proposed model against DL models and advanced algorithms on the MINI-DDSM and INBREAST datasets. Experimental results demonstrate that the system accuracy is significantly higher than other advanced algorithms. Figure 1 displays the birth year of cancer patients.

Subsequently, the discussion delves into the Residue Number System (RNS) for accelerating computationally intensive applications such as digital signal processing and neural networks by reducing the operand bit width (10-13). Remainders of a number divided by a collection of numbers known as moduli are used in RNS to represent numbers. Numbers that have each pair Mi and Mj as coprimes make up the set of moduli. Direct conversion is the act of dividing a number by the moduli set and expressing the resultant number by the remainders. This is known as inverse conversion—the process of translating RNS numbers back into the binary system. A large body of research, including, examines how various moduli sets affect the direct conversion stage's computational intricacy (14). The RNS domain allows for the direct execution of addition and multiplication, two common DNN operations (12). Each integer in RNS is less than the modulus since it represents the remainder of a division by a modulus. Consequently, RNS is a binary number that has several smaller, lower-bit numbers represented by it. The optimization of RNS operations' architecture has been the subject of several recent studies (15). RNS makes hardware implementation simpler by narrowing the operand bit width at the cost of more operations, which can lead to more parallelization.

Problem Statement

Early and precise detection of breast cancer using mammograms and ultrasound images is essential for effective treatment and improved patient outcomes. While these imaging techniques offer valuable insights, the

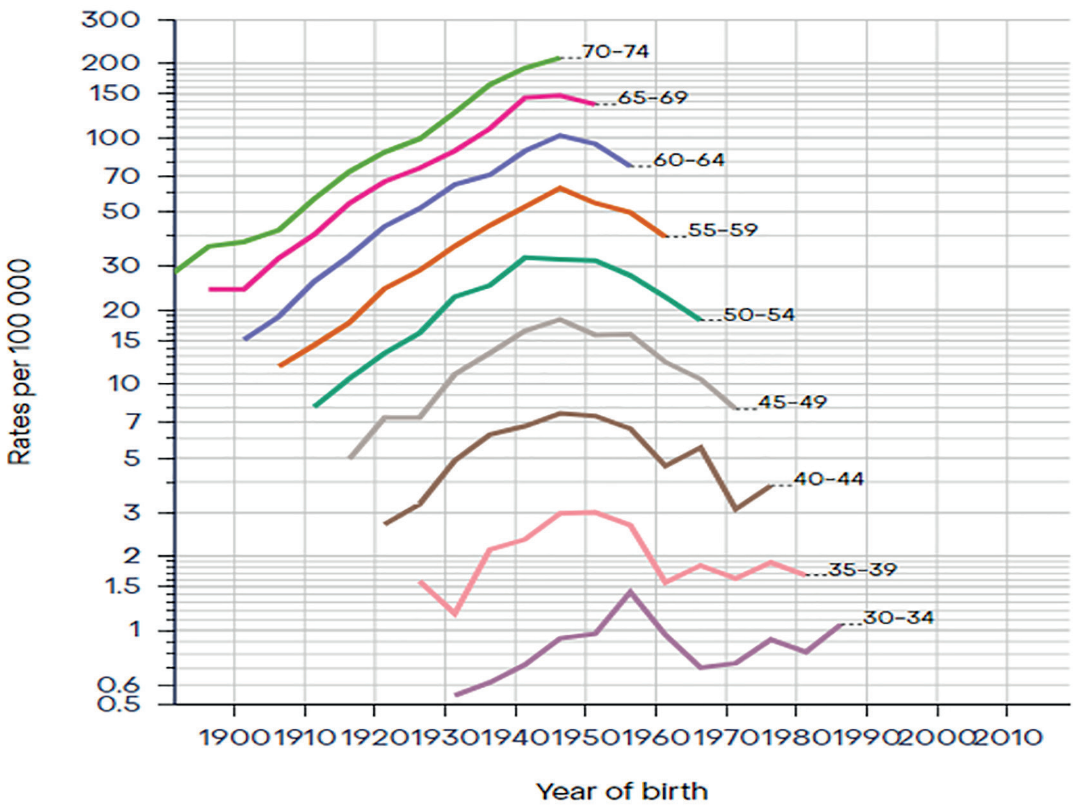

Figure 1: Year of birth of patients with cancer. Source: Globocan 2024.

potential for false results underscores the need for continuous advancements in diagnostic accuracy. Limitations of traditional machine learning techniques in detecting novel and complex tumors: Conventional machine learning (ML) techniques are commonly employed in tumor detection tasks due to their reasonable performance accuracy. However, these techniques have been criticized for their limitations in identifying novel and complex cancers. They often struggle with detecting complex cancers and differentiating them from normal tissue. The high rates of false positive and false negative diagnoses in imaging modalities can lead to patient anxiety, unnecessary medical procedures, and increased healthcare costs. Manual feature extraction from images can be time-consuming, tedious, and requires high expertise. The lack of an efficient and accurate method for real-time cancer detection in automated mammogram and ultrasound image diagnosis has driven the system towards the use of artificial intelligence methods for breast cancer diagnosis.

Contributions

We propose an entirely novel construction for deep artificial neural networks., RNS-ZFNET-ResNet-RNS, for accurate breast cancer detection from mammograms and ultrasound images. This hybrid architecture combines the strengths of CNNs in image analysis with the GPU-based potential of RNS to enhance speed, accuracy, and reduce computational complexity in capturing spatial relationships within image data. Our proposed method achieves high accuracy in distinguishing between benign, malignant, and normal breast tissue, surpassing the performance of numerous contemporary studies. By quantizing weights and activations using the RNS, we achieve significant improvements in computational efficiency, preventing overfitting and enhancing accuracy. Our method eliminates the need for time-consuming pre-processing steps and can classify both abnormal and normal mammograms. Our novel method utilizes the RNS for weight and activation quantization, leading to both accelerated computation and enhanced generalization capability. With no need for tumor segmentation, our technique provides a more efficient and effective workflow for breast cancer diagnosis. Our suggested end-to-end system has been extensively experimented on and has been found to surpass state-of-the-art techniques on various benchmark datasets. This approach is very efficient and simple to use, and it only needs preprocessed images, the hybrid network, and the RNS. We can very quickly train the model using the high-performance GPUs. The suggested architecture is tested on many datasets, and it works better than existing techniques. This study proposes a very nice novel approach to breast cancer diagnosis.

Literature Review

Deep learning has also been a revolution in medical image processing that will have far-reaching effects in disease detection and management. Computer-aided detection (CAD) systems utilizing machine and deep learning techniques to analyze ultrasound and mammography data have been a potent tool for breast cancer diagnosis. There is a great deal of promise for better patient outcomes with these developments. Zheng et al. presented a CNN-based automatic tumor region segmentation and breast cancer tumor detection approach from ultrasound pictures (16). Their system starts by eliminating typical situations using a pre-trained ResNet model. Next, for precise malignant tumor segmentation, the system uses an effective model known as Mask R-CNN. A deep learning model for classifying images of breast tissue stained with HE dyes was proposed by Rachlin et al. The authors used three pre-trained models (VGG16, InceptionV3, and ResNet50) to extract features, then combined the extracted features into a single feature vector using a 3-norm pooling technique (17). They also used a LightGBM classifier for 10-fold cross-validation classification, but the model only achieved an average accuracy of 87.2% across all folds. It is noteworthy that the authors used histological images for the classification of breast cancer. Kwak classified breast cancer on histological pictures using four advanced pre-trained models (VGG19, InceptionV3, InceptionV4, and ResNetV2) (7). A number of methods for data enhancement were used to improve the accuracy of the predictions. The models with the highest accuracy include Inception and ResNetV2, for the evaluation results. For binary and multi-class classification tasks, these models showed accuracies of 91% and 79%, respectively (2). For the multi-class breast cancer classification challenge, Wang et al. suggested a hybrid technique based on the InceptionV3 model. To arrive at the final forecast, this model included a majority voting system, a gradient raising mechanism, and other models that used logistic regression (16). A comparative examination of different techniques will be provided in Table 1.

Utilized extensively in numerous applications, neural networks have advanced on multiple platforms (20, 21). The use of quantization to accelerate and compress neural networks has been studied in the literature (19, 22-24). developed a program in that allows DNNs to be implemented in hardware and simulated in software using different data representations and approximation computing blocks (25). An automated DNN inference accelerator generator is put out by Kar, which quantizes the network first and then retrains it to recoup accuracy losses. Hardware-aware layer-wise weight quantization is achieved by Kar via reinforcement learning (19, 23).

The works discussed above utilize static quantization, in which the bit-width of weights is fixed at the network level or layer by layer. But according to research in, weights are quantized according to the difficulty of the input, guaranteeing that difficult inputs are handled by a more accurate network (24, 26). Research in quantize network weights to binary, -1, +1, displacing multiplications with XOR operations in order to further simplify neural network operation (27). Binarized neural networks are much faster than fixed-point alternatives, but because of their poor accuracy, they are not well suited for practical use (28, 29).

Table 1: Comparative Analysis of Different Approaches

Reference	Methodology	Limitations	Target Group Characteristics	Outcomes
Qian et.al. 2024 (18)	Researchers have used an evolutionary deep convolutional neural network (EDCNN) that is capable of learning and adapting itself over time."	This study delves into a new AI-powered method for breast cancer detection. The researchers utilized a deep convolutional neural network (CNN) in their investigation.	The study utilized breast ultrasound images from women undergoing routine screening or diagnostic evaluations. The study population was women of different ages with benign and malignant breast lesions in order to get a representative sample of breast abnormalities.	The results involved the classification accuracy of breast ultrasound images into classes (e.g., benign vs. malignant) and segmentation of breast lesions. The suggested CNN model worked better in classification than conventional methods, which indicates its potential for assisting radiologists.
Venkatesan et.al. 2019 (19)	Proposed modifications to ResNet and InceptionV3 versions	Its main objective is to detect cancer. The writers withheld the K-fold cross-validation performance. The classification accuracy is much inferior.	The research was based on a mammogram database of women, particularly those who have gone through breast cancer screening. The database contained images of women with different ages and risk factors, so it was a heterogeneous mammographic database.	The result was the establishment of a publicly accessible digital mammographic database with labels of different breast diseases. The database is a useful resource for research and development of machine learning algorithms for the detection and diagnosis of breast cancer.
Capra et.al. 2020 (20)	A group presented a classifier in low-contrast mammography	This method takes a long time since it involves multiplying matrix values in the CNN model and extracting features that are both CNN- and RNN-based.	The study analyzed mammograms from a diverse group of women, including those with different breast densities and varying risk profiles for breast cancer. The dataset aimed to include a representative sample of both normal and abnormal mammograms.	The results of the research were the creation of a deep learning-based mammogram classification system that was highly effective in the classification of abnormal and normal images. The research suggested the use of automated systems to assist radiologists in breast cancer screening for better diagnostic efficacy.
Cardarilli et.al. 2007 (10)	A group proposed a feature extraction technique, then a neural network for classification	Rather than concentrating on anomaly and malignancy identification simultaneously, this strategy focuses more on malignancy detection. K-fold cross-validation is substituted with a holdout strategy for performance evaluation.	The study focused on patients suspected of having COVID-19, characterized primarily by the presence of respiratory symptoms. The dataset included X-ray images from various sources, including public datasets and clinical cases, with a diverse demographic representation in terms of age and gender.	The primary outcome was the effectiveness of the combined deep CNN-LSTM model in accurately detecting COVID-19 from X-ray images. The model achieved high accuracy, sensitivity, and specificity, demonstrating its potential as a diagnostic tool in clinical settings.

Methods

Phase 1: IoT-enabled Request Logging and Transaction Processing

At this stage, all requests and transactions are registered and verified on the IoT platform. This method provides a framework for storing data and ensuring easy access.

Phase 2: Request Pattern Examination

At this stage, the data source analyzes the pattern of incoming requests. The system verifies if the submitted pattern correlates with the sent images and, if no pattern is detected, notifies the user and provides details of similar patterns.

Phase 2 Continued: Request Pattern Examination

In the second operation, the agent contacts the data source on the IoT platform to verify the recognition of the input pattern. A response message is then received indicating whether the pattern has been recognized. If detected, specific properties of the mammogram or ultrasound image are provided. If not recognized, the agent is informed of the non-recognition and provided with details about images similar to the input.

The next request processing step involves a deep learning algorithm. The data source not only verifies the pattern but also provides the agent with the image information of the incoming requests. In possession of this information, the agent approves or denies the request based on the output of the deep learning algorithm. The data source is composed of various datasets, each containing various data.

Phase 3: Machine Learning/Deep Learning Model

The features are chosen prior to model training using an improved PSO algorithm. The procedure is fundamental in order to further increase the efficiency and accuracy of the tumor detection system. RNS-RESNET and RNSZFNET networks work on the chosen features to make decisions on tumor types and body tissues.

Phase 4: Specifics of the Proposed Approach

In this phase, we proposed a completely new approach to breast cancer diagnosis. We presented a new approach to pre-processing and deep-learning-based breast cancer detection with pre-trained ZFNet-ResNet neural networks and an anonymized dataset. Then, we integrated the residual ZFNet-ResNet layers with an RNS in order to convert the residual layers.

Integration of RNS in the suggested design substantially improves computation efficiency. Quantizing weights and activations using RNS reduces computational complexity and memory requirements, enabling faster processing and making this method suitable for resource-constrained devices. This approach effectively prevents overfitting, a common issue in machine learning models that can lead to poor performance on unseen data. Because the RNS components of this design increase the model's capacity for generalization and decrease the dimensionality of the feature space, they help to prevent overfitting.

Typically, even with small datasets, a deep learning model exhibits promising performance because a pre-trained model (trained on a large dataset in the source domain) is only fine-tuned in the target domain (breast cancer detection). To ensure proper training and prevent overfitting, data augmentation (Image Data Generator) is employed. To reduce noise, enhance edges, and mitigate blurriness, pre-processing based on BM3D is employed to improve image quality. To address the issue of slow processing, a parallel GPU-based residue number system is utilized. The employment of a residue number system and the adjustment of the number of moduli accelerate the system, while skip connections facilitate deep network optimization. Additionally, ReLU is responsible for introducing non-linearity, leading to more accurate classification. Therefore, the proposed model demonstrates commendable performance, even with small and large datasets. An effective hybrid learning-based approach for the identification and categorization of breast cancer is proposed in this section. The importance of profound education Because deep learning algorithms may perform well with little data, they have become a popular tool for automated disease identification in recent years. Using the power of deep learning, we propose a novel network architecture for breast cancer detection that can achieve robust performance even with small datasets. Deep learning offers a solution to the problems faced by traditional deep learning networks, particularly when dealing with limited datasets. amounts of training data. As depicted in Figure 2, our proposed method provides an overview of the entire pipeline. The objective of this section is to achieve superior performance with a computationally efficient system.

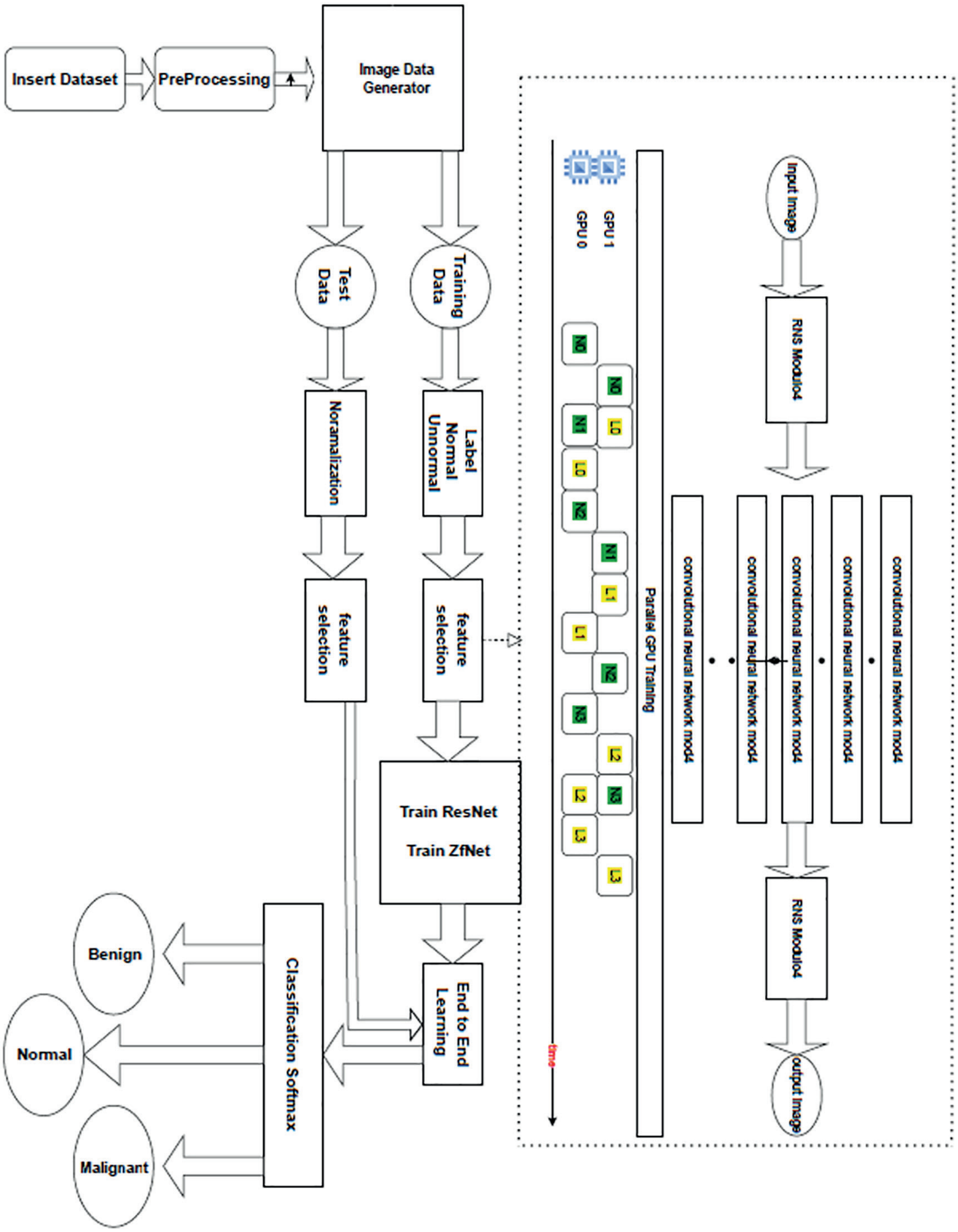

Figure 2: Schematic representation of the novel algorithm for segmenting breast tumors

The proposed method: Utilizes an efficient approach that combines three popular deep learning networks (ResNet, DenseNet201, ZFNET) with a residue number system. The system operates in two stages: abnormality detection - classifying breast images as normal or abnormal; malignancy detection - classifying abnormal images as benign or malignant. In this study, the pre-trained ZFNET was employed to extract informative features from mammographic images. Subsequently, the fully connected layers at the end of ZFNET were linked with an RNS layer.

Image Preprocessing

Let's explain the preprocess image function in more detail.

- **Normalization:** Pixel values are scaled to a specific range, such as 0 to 1, to ensure that all input data has a similar scale. This helps the model converge faster and more accurately.

- **Resizing:** Images are resized to a fixed dimension, like 224x224 pixels, to match the input requirements of the ZFNet, ResNet, models. This ensures that the model can handle images of equal sizes.
- **Cropping:** Random crops are extracted from the original images to generate a more diverse dataset. This process enables the model to learn stable features and reduces overfitting.
- **Rotation:** Images are rotated at various angles randomly to expose the model to varying object orientations. This helps the model learn objects from different points of view.
- **Reflection:** Random vertical or horizontal flipping of images is used to include mirror images. It makes the model generalize better and less sensitive to orientation.

Machine Learning/Deep Learning Algorithm

Here, before training the three models, we use feature selection using a modified Particle Swarm Optimization (PSO) algorithm. The aim is to reduce the training time, prevent overfitting, and improve the accuracy of the models.

Results

The proposed method maps neural network implementation to the RNS domain to reduce the complexity of DNNs without affecting the accuracy of the quantized network. To test the proposed method, two popular network architectures, ZFNET and RESNET, were realized in Python. For training and quantizing the networks, we employed the proposed method in (20). The proposed method is tested on two different datasets, namely MINI-DDSM and INBREAST (13, 30). The results so derived are compared with those of earlier investigations (31-35). This comparative analysis aims to evaluate the effectiveness and performance of the proposed method against existing approaches on both the MINI-DDSM and INBREAST datasets. All evaluations were conducted on a Colab environment with a T4-GPU and 16GB RAM. For training the RNS-ZFNET and RNS-RESNET networks, the following hyperparameters were used: learning rate of 0.001, batch size of 64, and the model was trained with the Adam optimizer for 100 epochs. and cross-entropy loss function. The Particle Swarm Optimization (PSO) algorithm was used with a population size of 100 and a maximum of 200 iterations.

Analysis of Results

Figure 2 depicts the changes in training and validation accuracy, as well as the training and validation loss, for two separate datasets: INBREAST and MINI-DDSM.

INBREAST dataset: Training accuracy commences at approximately 75% and consistently increases with each epoch, reaching 99%. Similarly, validation accuracy starts at 84% and exhibits a comparable upward trend, attaining 91.5% at the 40th epoch. Both metrics demonstrate continuous improvement throughout training, indicating effective learning and generalization on the INBREAST dataset.

The training and validation loss, initially high, gradually decreases with each epoch. This reduction indicates the network's ability to minimize the discrepancy between predicted and actual values, signifying continuous improvement in prediction performance on the INBREAST dataset.

MINI-DDSM dataset: Training accuracy commences at 81% and gradually increases until the 40th epoch, reaching 98%. Similarly, validation accuracy starts at 82% and follows a comparable upward trend, attaining 95.02% at the 40th epoch.

Although both metrics exhibit improvement, the rate of improvement slows down after the 28th epoch, indicating that the proposed hybrid network effectively learns patterns in the MINI-DDSM dataset but experiences diminishing returns over time. The initial training and validation loss is relatively high and gradually decreases in subsequent epochs.

This decrease demonstrates the proposed network's effectiveness in minimizing the errors between predicted and actual values in the MINI-DDSM dataset. However, similar to the accuracy trend, the rate of loss reduction also slows down after the 23rd epoch. Tables 2, and 3 compare the proposed method with other approaches in terms of precision, recall, overall accuracy, and F1-score on the INBREAST dataset.

Precision, Recall, and F1-Score: As depicted in Figure 3, the proposed method and other approaches exhibited superior performance on the INBREAST dataset compared to the MINI-DDSM dataset. This can be attributed to the

Table 2: The performance metrics

Metrics	Formula
Precision: measures how well a model performs in correctly identifying positive cases without including false positives (3).	$Prec.=\frac{TP}{FP+TP}$
Recall: quantifies how well a model identifies positive cases without missing any true positives (36).	$Rec.=\frac{TP}{FP+FN}$
F1-Score: offers a thorough assessment of a model's effectiveness in terms of capturing all pertinent positive events and making positive predictions (37).	$F1-Score=\frac{2\times Prec.\times Rec.}{Prec.+Rec.}$
Accuracy: quantifies the overall correctness of predictions, which is calculated by (4).	$Accuracy=\frac{TP+TN}{Total\ Instances}$
Detection rate: The metric assesses the percentage of positive cases accurately detected by a system (5).	$DR=\frac{TP}{TP+FN}$
False alarm rate: measures the rate at which the system produces false positive predictions or detections (38).	$FAR=\frac{FP}{FP+TN}$

Table 3: Comparison of performance for benign detection in the MINI-DDSM and INBREAST dataset

Method	MINI-DDSM dataset				INBREAST dataset			
	Accuracy (%)	Score F1	Sensitivity (%)	Precision (%)	Accuracy (%)	Score F1	Sensitivity (%)	Precision (%)
ZFNET	0.9404	0.9573	95.00	96.48	0.9117	95.38	87.32	0.9117
ResNet18	0.8815	0.9286	95.00	90.81	0.9126	92.31	90.23	0.9126
RNS-ZFNET	0.9235	0.9614	94.00	94.20	0.9163	94.31	88.45	0.9163
RNS-ResNet18	0.9341	0.9145	95.00	97.25	0.9185	94.65	88.51	0.9185

Table 4: Comparison of performance for anomaly detection in MINI-DDSM and INBREAST datasets

Method	MINI-DDSM dataset				INBREAST dataset			
	Accuracy (%)	Score F1	Sensitivity (%)	Precision (%)	Accuracy (%)	Score F1	Sensitivity (%)	Precision (%)
ZFNET	0.9831	0.9862	98.25	98.96	0.9404	0.9573	95.00	96.48
ResNet18	0.9852	0.9900	98.75	99.25	0.8815	0.9286	95.00	90.81
RNS-ZFNET	0.9911	0.9931	98.71	98.99	0.9235	0.9614	94.00	98.20
RNS-ResNet18	0.9984	0.9921	98.65	99.23	0.9341	0.9145	95.00	97.25

higher number of records in the INBREAST dataset, which presents a more complex learning challenge than the MINI-DDSM dataset.

Accuracy: The RNS network's ability to reduce complexity and enhance its understanding of temporal dependencies has improved its predictive capabilities. Consequently, the proposed model has demonstrated superior performance.

Table 4 and 5 compare the proposed method with other approaches in terms of precision, recall, overall accuracy, and F1-score on the MINI-DDSM dataset.

The proposed approach consistently outperforms other methods in evaluating cancer diagnosis on the MINI-DDSM dataset. This is evident through the evaluation of accuracy, recall, overall precision, and F1-score across various tumor types.

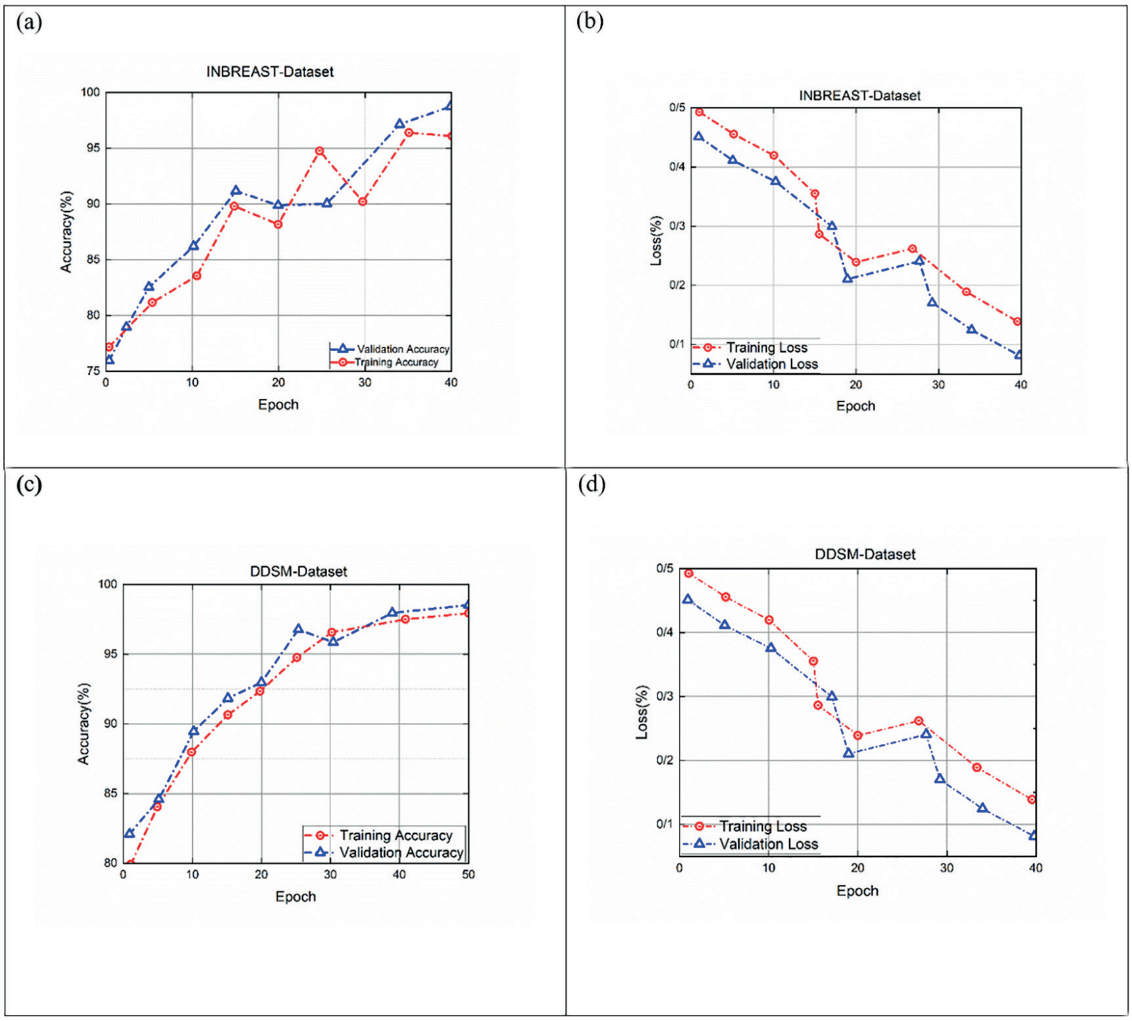

Figure 3: (a) Training and validation accuracy for the INBREAST dataset. (b) Training and validation loss for the INBREAST dataset. (c) Training and validation accuracy for the MINI-DDSM dataset. (d) Training and validation loss for the MINI-DDSM dataset.

Table 5: Benign detection in the MINI-DDSM and INBREAST datasets

Method	MINI-DDSM dataset				INBREAST dataset			
	Score F1	Recall (%)	Precision (%)	Accuracy (%)	Score F1	Sensitivity (%)	Precision (%)	Accuracy (%)
ZFNET	0.8889	86.00	91.98	92.83	0.8240	79.23	85.83	88.72
ResNet18	0.9016	87.00	93.55	93.67	0.4616	43.85	48.72	65.90
RNS-ZFNET	0.9262	91.00	94.30	95.17	0.8594	84.62	87.3	90.77
RNS-ResNet18	0.9238	94.00	90.82	94.83	0.8792	85.01	86.00	91.20

The proposed method demonstrates a notable accuracy, indicating high prediction correctness, as well as high recall values, signifying its ability to identify a substantial portion of cancers. In comparison, while competitive, other methods such as ZFNET, RESNET, and DENSNET exhibit slightly lower accuracy, recall, and overall precision.

The observed superiority of the proposed method can be attributed to several factors. Comparing results on the INBREAST dataset, it is clear that accuracy, recall, and overall precision values are generally higher on the MINI-DDSM dataset. This discrepancy might be due to the higher complexity of the INBREAST dataset, characterized by diverse tumor patterns and potential class imbalances. The proposed method, adept at handling these complexities, demonstrates consistent and superior performance across various attack scenarios. Tables 6-8 compare the performance with existing CAD models on ultrasound and mammography datasets.

Table 6: Comparison of time spent (in seconds) between datasets

Method	MINI-DDSM	INBREAST
ZFNET	0.094	0.162
ResNet18	0.015	0.037
RNS-ZFNET	0.180	0.040
RNS-ResNet18	0.064	0.118

Table 7: Comparison of performance with existing CAD models on mammography datasets

Existing methods	Accuracy	
	DDSM	INBREAST
Deep ensemble TL (31)	88.00	49.47
Deep ensemble TL (31)	67.00	90.26
CNN with pretraining (32)	89.56	91.00
CASEADEDeep Learning (33)	89.32	91.00
RNS-ZFNET	89.06	91.02
RNS-ResNet18	89.01	91.02

Table 8: Comparison of performance with existing CAD models on ultrasound datasets

Existing methods	Accuracy	
	BUS_1	BUS-2
ResNet (34)	73.00	90.47
DenseNet (34)	73.00	89.47
CNN-AlexNet (35)	99.38	78.00
TL-Inception (35)	98.75	85.00
RNS-ZFNET	98.80	77.00
RNS-ResNet18	98.60	85.02

Discussion

The results presented in this study demonstrate the effectiveness of the proposed hybrid deep learning approach, integrating Convolutional Neural Networks (CNNs) and Residual Number Systems (RNS), for enhancing breast cancer detection across two distinct datasets: INBREAST and MINI-DDSM. The performance metrics indicate that our method consistently outperforms traditional models, showcasing significant improvements in accuracy, precision, recall, and F1-score. Recent studies have demonstrated the effectiveness of hybrid deep learning approaches for breast cancer detection. Sharmin et al. combined ResNet50V2 with ensemble-based machine learning, achieving 95% accuracy on histopathology images (39). Sahu et al. proposed hybrid CNN classifiers, with their ShuffleNet-ResNet framework outperforming state-of-the-art methods on mammogram and ultrasound datasets, reaching up to 99.17% accuracy (40). Altaf developed a hybrid model integrating Pulse-Coupled Neural Networks and CNNs with transfer learning, achieving 98.72% accuracy on the DDMS dataset (41). Raaj presented a hybrid CNN architecture incorporating radon transform and data augmentation, attaining 99.17% accuracy on the MIAS dataset (42). These studies consistently show that hybrid deep learning approaches, combining various neural network architectures and preprocessing techniques, significantly improve breast cancer detection accuracy across different imaging modalities and datasets.

The training dynamics of both datasets reveal significant information regarding the learning potential of the hybrid model. As can be seen for the INBREAST dataset, the training accuracy reached a staggering 99% at the 40th epoch, with the validation accuracy reaching a peak of 91.5%. This consistent upward trend for both validation and training metrics is a sign of successful learning and generalization and suggests that the model is very suitable for the complexities of the INBREAST dataset, such as heterogeneous tumor patterns and potential class imbalances. The incremental decline in both validation and training loss also helps to further reinforce the model's suitability in minimizing prediction errors, suggesting its capability in handling complex data. Recent research has investigated hybrid deep-learning models for the detection of breast cancer from mammography images. Hybrid models benefit from the strengths of multiple approaches to attain higher accuracy and efficiency. Altaf suggested a hybrid approach using Pulse-Coupled Neural Networks and CNNs with high accuracy on various datasets (41). Swetha et al. proposed a system with weight factors and threshold values to develop an efficient hybrid model with 99.69% accuracy and less processing time (43). Aslan proposed a CNN and Bidirectional Long Short Term Memories-based hybrid end-to-end learning system with 98.56% accuracy on the MIAS dataset (44). Alzubaidi et al. utilized same-domain transfer learning and a hybrid model of parallel convolutional layers and residual connections, and attained 97.4% image-wise classification accuracy on the ICIAR-2018 dataset (45). These researches demonstrate the potential of hybrid models in enhancing the accuracy and efficiency of breast cancer diagnosis.

On the contrary, the MINI-DDSM dataset showed quite a different learning curve. Although the training accuracy achieved 98% and validation accuracy reached 95.02%, the improvement rate started slowing down after epoch 28. This indicates that although the hybrid model is able to learn effectively from the MINI-DDSM dataset, the comparatively less complex nature of the dataset could be a cause for performance gain saturation. The high initial loss values followed by a consistent declining trend also point towards the capability of the model to make increasingly good predictions at diminishing returns with time. Various strategies have been investigated in literature in recent times to maximize deep learning performance using small medical image datasets for diagnosing breast cancer. Transfer learning works effectively with limited data, and a paper has reported 98.72% accuracy on the DDMS dataset using a hybrid Pulse-Coupled Neural Networks and Convolutional Neural Networks model (41). A paper also discovered that one-cycle training, discriminative learning rates, and progressive freezing of layers resulted in the highest performance with small datasets (46). High-frequency monitoring of neural network learning curves during training has been suggested to comprehend the development of model performance (47). Besides, a discriminative fine-tuning strategy with dynamic layer-wise learning rates coupled with mixed-precision training and data augmentation has been effective for mammogram classification with DenseNet at 99.8% accuracy (48). These techniques are important indicators for enhancing the performance of deep learning models on small medical imaging data.

The comparison of the performance measure of the two datasets reveals that the suggested approach performs better in the MINI-DDDSM dataset with better accuracy, recall, and precision than state-of-the-art models such as ZFNET and ResNet18. The reason is that the model can overcome the complexities of the data by leveraging the capabilities of RNS to further its comprehension of temporal relationships and lessen computational complexity. The increased accuracy and recall rates indicate not just that the method proposed here is efficient in classifying breast cancer cases but also that it is efficient in reducing false negatives, which in clinical practice is of utmost importance. Recent research work has investigated sophisticated methods to enhance breast cancer detection in mammography. Yu et al. suggested an ensemble fuzzy model with multiple deep-learning classifiers of high accuracy on DDSM (0.97) and BACH (97.05%) datasets (49). Sahu et al. presented hybrid CNN classifiers, whose ShuffleNet-ResNet model achieved state-of-the-art mini-DDSM, BUSI, and BUS2 dataset performance up to 99.17% accuracy (40). With deep learning CNNs, Aboutalib et al. discriminated recalled-benign mammography images from negative and malignant images with 0.70-0.96 AUCs on various datasets (50). These experiments demonstrate the potential of cutting-edge machine learning techniques to enhance the accuracy of breast cancer detection and reduce false positives in mammography screening.

The findings also indicate the challenge posed by the INBREAST dataset. While the model is extremely good, the complexity and heterogeneity of tumor presentations can be the cause of the relatively lower overall precision and recall of the MINI-DDSM dataset. This reflects the significance of features in the dataset on model performance and implies that additional refinement of the training process or model architecture might be required to fully unlock the potential of the INBREAST dataset. Deep learning techniques have reported promising results in diagnosing breast cancer from mammography datasets. Research has reported high performance on publicly available datasets such as DDSM and INbreast with AUC ranging from 0.78 to 0.93 (51). However, translating these models to clinical practice remains challenging due to the differences in dataset characteristics and the intricacies of real-world cases (52). The INbreast dataset, although small, has been helpful to evaluate the performance of models, with some studies reporting high accuracy and AUC values (53). Several approaches have been tried by researchers to improve model performance, including data augmentation, transfer learning, and use of deeper neural networks (53). In spite of these developments, the requirement for bigger, more varied datasets that more accurately reflect contemporary clinical practice continues to be a substantial challenge in the discipline (52).

In addition, the side-by-side comparison of Tables 2 and 4 demonstrates the excellence of the proposed method compared to state-of-the-art methods. The higher precision, recall, and F1 scores across the board consistently show that our hybrid model is better at breast cancer diagnosis across different types of tumors. This is especially important in clinical practice, where the correct determination of malignancies can directly impact patient prognosis.

Conclusion

In conclusion, the proposed hybrid deep learning approach shows promising results in breast cancer detection, and more particularly in the MINI-DDSM dataset context. While the model shows excellent prospects for application in the clinic, more studies should be conducted to further optimize its performance on harder datasets such as INBREAST. Future research may delve into sophisticated strategies like data augmentation, transfer learning, or ensemble techniques to further enhance the model's robustness and generalization capabilities in various imaging conditions. In general, the results add to the body of knowledge Joining the existing literature in recommending the incorporation of deep learning methods in medical diagnosis, towards making more precise and effective breast cancer detection systems a reality.

Authors' Contribution

Behnam Rezaei Bezanjani: Conceptualization, Data curation, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. Seyyed Hamid Ghafouri and Hamid Reza naji: Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Visualization, Writing - review & editing.

Ethical Approval

The protocol of the study adhered to the ethical guidelines of the 1975 Declaration of Helsinki, which was revised in 1983. The authors affirm that informed consent was received from the legal next of kin of the deceased prior to preparing this report. Private information, including name and surname was removed from the data sheet to comply with ethical concerns.

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Conflict of Interest

There are no conflicts of interest.

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