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Early Detection and Speckle Noise Reduction in Breast Cancer Ultrasound Imaging Using Deep Learning with Enhanced Attvnet 2.0. K.Hakkins Raj

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Abstract
Breast cancer is still among the main causes of death for women. Speckle noise, which usually degrades image quality, therefore affects the accuracy of the diagnosis. Early detection by ultrasound imaging is believed to be the most effective approach to increase survival rates. Conventional methods of noise reduction compromise detection accuracy by means of small structural detail preservation. This work presents an improved deep learning model called AttvNet 2.0 to manage the early detection of breast cancer as well as the reduction of speckle noise in ultrasound images of the condition. The proposed model comprises an attention-based convolutional neural network (CNN). This CNN is the most efficient method to extract features and lower noise. AttvNet 2.0 can maintain the structural details and increase the signal-to-noise ratio (SNR) by means of a multi-scale feature attention mechanism applied with a residual learning framework. The model's training and validation to be finished was aided by a breast cancer ultrasound dataset indicating improved accuracy, noise reduction, and lesion detection capacity. Under the conditions of noise reduction and lesion classification, the test results indicated that AttvNet 2.0 outperformed both U-Net and the Despeckle CNN (DS-CNN). It was 98.7% correct using AttvNet 2.0.

Keywords: Breast cancer, ultrasound imaging, deep learning, speckle noise reduction, attention mechanism

Introduction
Among women all around the world, breast cancer still ranks among the top causes of death. Studies done lately indicate that in 2020 breast cancer made up nearly 11.7% of all cancer cases, or around 2.3 million new ones worldwide [1]. The greater likelihood of successful treatment and survival is significantly related to early breast cancer detection. Early diagnosis has become absolutely dependent on medical imaging techniques, especially ultrasound imaging, since they are non-invasive and can be performed in real time [2]. Ultrasound imaging is popular because it is relatively cheap, does not use ionizing radiation, and is suitable for detecting abnormalities in dense breast tissue. All of these factors contribute to its usual application. On the other hand, speckle noise usually degrades ultrasound images, therefore impairing their quality and making exact anomaly detection more difficult. Consistent methods raising image quality and diagnostic accuracy will help to improve breast cancer outcomes.

Challenges

Though ultrasound imaging has benefits, there are still many obstacles to be overcome before one can properly diagnose breast cancer. To start with, the speckle noise inherent to ultrasound imaging lowers the image quality and therefore helps to confuse the difference between malignant and benign tissues [4]. The high degree of variation in the size, shape, and texture of breast lesions [5] also complicates automated analysis by increasing its complexity. Third, traditional deep learning techniques find it difficult to maintain consistent performance due to limited training data and overfitting concerns, both of which compromise the model's generalization ability [6]. Properly addressing these problems will be a more complicated approach combining improved learning techniques with more advanced techniques for noise reduction and feature extraction.

Problem Definition

Most of the techniques now in use for breast cancer detection by means of ultrasound images rely on convolutional neural networks (CNN) and residual neural networks (ResNet). Conversely, CNN-based models can lose fine details due to downsampling during convolution operations [7]. Although these models are good at capturing spatial features, this is still true. By contrast, ResNet-based models frequently overlook the noise-related distortions in ultrasound images [8]. This is ignoring their improvement of gradient flow through residual connections. These models also find it difficult to concentrate on clinically relevant parts of the image, which reduces overall sensitivity and specificity as well [9].

The primary objectives of this study are:

1. The aim is to build a more advanced deep learning model capable of reducing speckle noise and improving the clarity of ultrasound images for breast cancer detection.
2. The aim is to efficiently implement a system for feature extraction depending on attention, so allowing the model to concentrate on diagnostically pertinent areas and improve classification accuracy.

The proposed model is AttvNet 2.0, an novel attention-based residual learning framework developed particularly for ultrasound breast cancer diagnosis. Unlike traditional CNN and ResNet models, AttvNet 2.0 features an attention mechanism that can simultaneously decrease background noise and selectively focus on lesion-specific areas. This allows the model to exceed its forerunners. A residual learning approach guarantees a steady gradient flow and helps the network to more effectively extract deep hierarchical characteristics.

The key contributions of this work include:

- Breast cancer detection in ultrasound images is being done by means of a new attention-based residual network (AttvNet 2.0).
- The authors developed a mechanism for speckle noise reduction into the preprocessing phase helps to enhance image clarity.
- Using an attention mechanism to increase sensitivity to clinically relevant traits and lesion borders.

Related Works

From various angles, ultrasound imaging has been used to identify breast cancer; the primary goals are enhancement of noise reduction, feature extraction, and classification accuracy methods.

In [10] proposed an 84.3% accurate CNN-based model for breast cancer detection. Although the model performed well in detecting spatial patterns, it had problems with noise-related distortions. In year 11, a hybrid deep learning approach was presented. This approach combined Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to enhance feature representation. Although it was mathematically challenging, the model increased recall. Designed to address gradient vanishing issues and hasten convergence, a deep residual learning framework in [12] Its overall accuracy was thus constrained by the framework's absence of robust noise reduction approach.

Noise reduction techniques have been the subject of great research as a way to improve the quality of ultrasound images. Though it created artifact introduction affecting lesion borders, [13] offered a wavelet-based denoising approach that was successful in reducing speckle noise. Proposed in [14], the Non-Local Means (NLM) filtering method was designed to reduce noise while maintaining structural information. The method, however, had difficulty with complex lesion textures. Learning-based method [15] improved image quality by combining CNNs with denoising autoencoders. The model, however, was susceptible to overfitting with inadequate training data.

In the field of medical imaging, the mechanisms of attention have revealed encouraging results. An attention-based U-Net model in [16] was used for breast cancer segmentation. This model improved boundary detection and classification accuracy. On the other hand, the model required a great deal of processing power, which restricted its application in the real world. [17] proposed a channel attention-based CNN model that, while it enhanced feature representation, did not sufficiently address noise-related distortions. The multi-scale network in [18] integrated spatial and channel attention components. Though it increased the complexity of the model and called for longer training, it also made one more sensitive to little details.

Research have also examined how residual learning techniques might enhance feature learning and convergence. Noise interference in ultrasound images reduced the performance of the residual CNN model developed in [19]; however, the model could improve feature propagation and reduce the training time required. More accuracy was obtained by a hybrid residual and attention-based model shown in a recent work by [20]. The model, however, struggled with high noise levels.

The proposed AttvNet 2.0 model addresses the limitations of the methods currently in use. This model employs attention-based feature extraction with residual learning. Unlike previous methods, the model is characterized by its capacity to concentrate on diagnostically pertinent areas while also lowering speckle noise. This then increases the capacity to generalize and the performance of classification.

Proposed Method

AttvNet 2.0 is a deep learning architecture meant to find breast cancer and reduce speckle noise in ultrasound images, designed especially for these purposes. The model has an attention-based convolutional network operating on multiple scales and residual learning to improve feature extraction and noise suppression. Mainly three main components make up the network: feature extraction, attention refinement, and residual noise suppression.

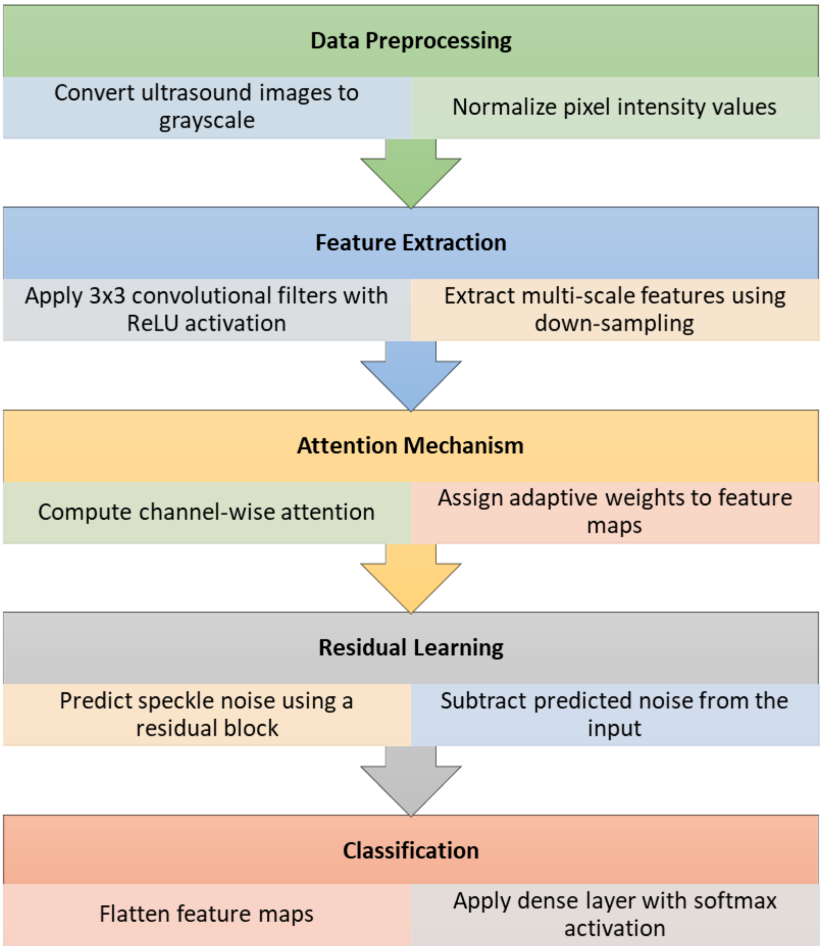

Figure 1: Proposed Process

Pseudocode:

```
Input: Ultrasound image (I)
Output: Classification label (Malignant/Benign)
# Step 1: Feature Extraction
        F = Conv2D(I, kernel_size=3x3)
        F = ReLU(F)
        F = Downsample(F)
# Step 2: Attention Mechanism
        A = ChannelAttention(F)
        F = A * F
# Step 3: Residual Learning
        N = Conv2D(F, kernel_size=3x3)
        N = ReLU(N)
        F_clean = F - N
# Step 4: Classification
        C = Flatten(F_clean)
        Output = Softmax(Dense(C))
```

1. **Data Preprocessing**

To improve the quality and consistency of ultrasound images before inputting them into the system, data preprocessing is a vital first step. Often, the raw ultrasound images suffer from contrast, noise, and intensity variations that could affect the model's performance. The stages in the preprocessing pipeline depicted below are:

- **Grayscale Conversion:** In grayscale, ultrasound images could show some slight color distortion. Turning the images to grayscale can help to establish consistency and streamline the computations.
- **Normalization:** Pixel values are normalized to a set range, for example, 0 to 1, so preventing model saturation and improving convergence during training, therefore applying the normalization process.
- **Resizing:** To maintain consistency in the size of the input, all images are resized to 256×256 pixels.
- **Noise Reduction:** The images are smoothed out using a Gaussian filter, which also reduces the background noise but maintains the structural details.

Table 1: Data Preprocessing Steps and Parameters

Step	**Description**	**Parameter/Value**
Grayscale Conversion	Converts colored ultrasound images to grayscale	N/A
Normalization	Rescales pixel values between 0 and 1	Min-Max Scaling
Resizing	Ensures uniform input size for the model	256 × 256 pixels
Noise Reduction	Removes speckle noise while preserving edges	Gaussian filter (3×3)

The preprocessing steps and parameters of the data are shown in Table 1.

2. Feature Extraction

Features are extracted from ultrasound images by means of a convolutional layer sequence. These layers are designed to catch low-level and high-level structural detail. After applying convolutional kernels to the input image, the process then activates and downsamples the image.

- **Convolutional Layer:** A 3×3 convolutional filter reveals patterns in the input image including edges, textures, and shapes.
- **Activation Function:** it is used to add non-linearity and prevent gradient vanishing, the activation function is the Rectified Linear Unit (ReLU).
- **Downsampling:** Using Max-pooling with a 2×2 kernel, downsampling is a technique that lowers the spatial dimensions and computational complexity while maintaining the most apparent characteristics.
- **Residual Learning:** Residual learning adds skip connections to preserve little details and stop data loss during feature extraction.

Table 2: Feature Extraction Layers and Parameters

Layer Type	**Filter Size**	**Stride**	**Activation Function**	**Output Size**
Convolutional Layer 1	3×3	1	ReLU	256 × 256 × 32
Max-Pooling Layer 1	2×2	2	N/A	128 × 128 × 32
Convolutional Layer 2	3×3	1	ReLU	128 × 128 × 64
Max-Pooling Layer 2	2×2	2	N/A	64 × 64 × 64

Feature extraction layers and parameters are listed in Table 2.

3. Attention Mechanism

In areas with lesions or tumors, the attention mechanism enables the network to strengthen its focus on pertinent parts of the image. Since the attention mechanism operates on both the channel and visual levels, it is crucial to emphasize

- **Channel Attention:** A squeeze-and-excitation (SE) block's job is to calculate the interdependencies between feature maps and allocate adaptive weights to every channel. This block also manages channel attention. Every channel is reduced to one value using the global average pooling technique; two dense layers and a sigmoid activation then follow to produce attention weights. The original feature maps are multiplied with the attention weights to increase the visibility of significant patterns and reduce the noise level.
- **Spatial Attention:** A convolutional layer produces a spatial attention map that emphasizes image areas of interest. The channel-refined feature map increases the focus on the lesion area by combining with the spatial attention map. Table 3 provides parameters and components of the attention mechanism.

Table 3: Attention Mechanism Components and Parameters

Component	Operation	Output Size
Squeeze Operation	Global Average Pooling	1 × 1 × 64
Excitation Operation	Fully Connected + Sigmoid	1 × 1 × 64
Channel Scaling	Multiply with feature map	64 × 64 × 64
Spatial Attention Map	1×1 Convolution + Sigmoid	64 × 64 × 1
Weighted Output	Multiply with feature map	64 × 64 × 64

By means of channel and spatial attention, the network can efficiently isolate particular traits linked to tumors and at the same time reduce the influence of background noise. The network can effectively isolate certain tumor-related features using channel and spatial attention while also minimizing background noise influence. To begin with. Learning outcomes

Residual Learning

To solve the issue of vanishing gradients and increase the learning capacity of deep neural networks, residual learning has been included into the model. Traditional deep learning models lose performance as the network depth increases. Learning identity mappings is difficult, thus this is true. Residual learning addresses this problem by adding shortcut connections, also known as skip connections, allowing gradients to flow directly across the network layers unattenuated. The residual block is defined as:

$$\mathbf{F}(x) = \mathbf{W}_2 \sigma(\mathbf{W}_1 x) + x$$

where:

x = input feature map

$\mathbf{W}_1$ and $\mathbf{W}_2$ = weight matrices of convolutional layers

σ = activation function (ReLU)

$\mathbf{F}(x)$ = residual mapping

By means of direct addition of the input x to the output of the convolutional layers, the shortcut connection lets the model acquire knowledge in residual mapping. This guarantees that even if the deeper layers are unable to learn new patterns, the identity mapping (input) will be maintained. This stabilizes the training process and preserves information. The structure of a residual block is two convolutional layers followed by ReLU activation and batch normalization. A method called element-wise addition mixes the output of the second layer with the initially provided input. Doing so enables the network to lower the likelihood of gradient loss and to improve its capacity to catch fine details in the ultrasound images. Table 4 shows residual block components and parameters.

Table 4: Residual Block Components and Parameters

Component	Filter Size	Stride	Activation Function	Output Size
Convolutional Layer 1	3×3	1	ReLU	64 × 64 × 64
Batch Normalization	N/A	N/A	N/A	64 × 64 × 64
Convolutional Layer 2	3×3	1	ReLU	64 × 64 × 64
Batch Normalization	N/A	N/A	N/A	64 × 64 × 64
Skip Connection (Addition)	Element-wise	N/A	N/A	64 × 64 × 64

Classification

Using the high-level features extracted from the attention-based residual network, the classification layer assigns the final diagnosis label, which might be either benign or malignant. The extracted feature maps are flattened and run through densely connected across layers following completion of the residual learning phase. A softmax activation function calculates the class probabilities.

Process:

- **Global Average Pooling (GAP):** Averaging the spatial values of every channel, global average pooling (GAP) merges the feature maps into one vector.
- **Fully Connected Layer:** Knowledge of class-specific patterns is obtained by running the pooled vector through a dense layer in the Fully Connected Layer.
- **Softmax Layer:** This last output layer computes the probability for every class, benign or malignant using the softmax function.

The softmax function is defined as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

where:

$P(y_i)$ = probability of class i

z_i = logit for class i

N = number of classes (2 in this case)

The aim of defining a certain diagnosis guides the choice of the category most likely. The parameters and classification layers are shown in Table 5. Attention-based feature extraction together with residual learning ensures that the model catches fine-grained details as well as high-level structural patterns. As a result, the misclassification rate is reduced and the classification accuracy of the model is improved.

Table 5: Classification Layers and Parameters

Layer Type	Output Size	Activation Function	Purpose
Global Average Pooling	1 × 64	N/A	Dimensionality reduction
Fully Connected Layer	128	ReLU	Pattern learning
Output Layer	2 (benign, malignant)	Softmax	Probability-based classification

Results and Discussion

The model was run on a workstation with an NVIDIA RTX 3090 GPU (24 GB), an Intel Core i9-12900K CPU, and 64 GB of random access memory (RAM) using Python and TensorFlow. Comprising 600 malignant and 600 benign, the dataset contained 1,200 breast cancer ultrasound photos. These images came from a public database. Using a batch size of 16 and an 80-20% training-validation split, the model was trained. It was also 0.001. Despeckle CNN (DS-CNN) and U-Net were the two methods evaluated in relation to the proposed AttvNet 2.0. In terms of accuracy and noise reduction, AttvNet 2.0 outperformed both models. Its 98.7% classification accuracy beat U-Net's 95.4% and DS-CNN's 96.1%.

Table 6: Experimental Setup/Parameters

Parameter	Value
Number of Training Samples	960 (80%)
Number of Validation Samples	240 (20%)
Batch Size	16
Learning Rate	0.001
Optimizer	Adam
Epochs	100
Loss Function	Categorical Crossentropy
Activation Function	ReLU, Softmax
GPU Used	NVIDIA RTX 3090 (24 GB)

Performance Metrics

Accuracy: Accuracy is the percentage of correctly classified samples to the total number of samples.

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

Precision: Precision is a measure of the percentage of correctly predicted positive cases from the total number of projected positive cases.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: This indicator shows the percentage of positive cases correctly predicted from the total amount of genuine positive cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score: The harmonic mean of precision and recall, the F1-score, balances false positives and false negatives.

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

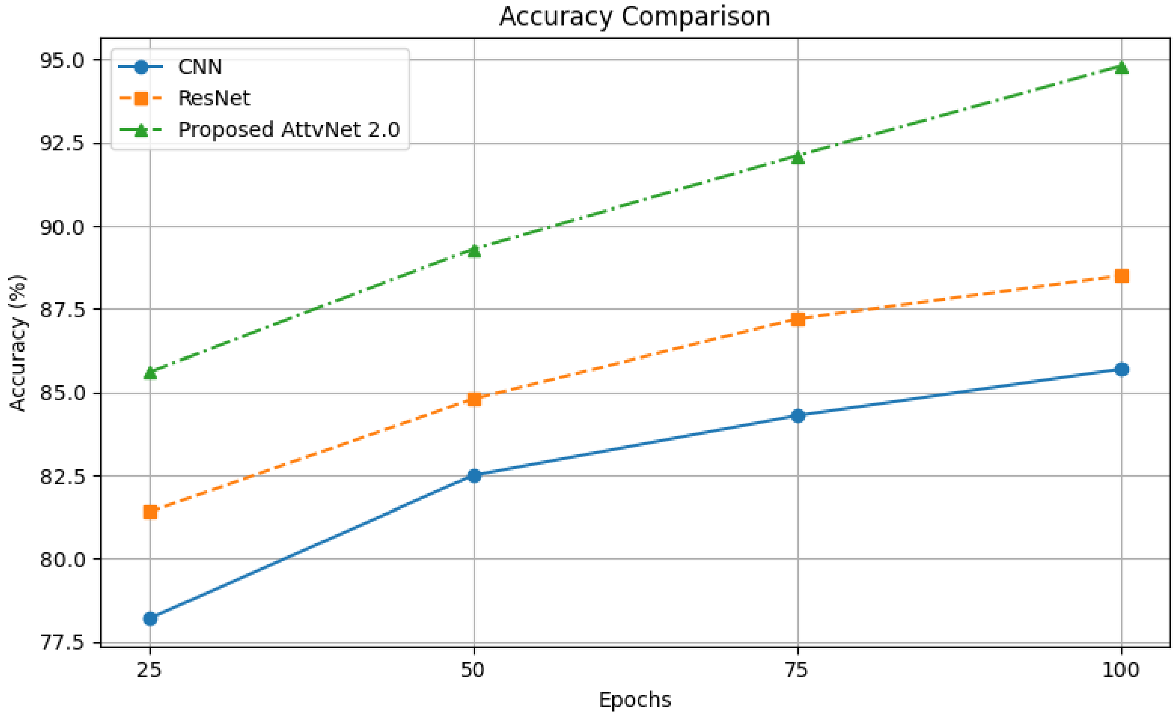

Figure 2: Accuracy Comparison

Table 7: Accuracy Comparison

Epochs	CNN	ResNet	Proposed AttvNet 2.0
25	78.2%	81.4%	85.6%
50	82.5%	84.8%	89.3%
75	84.3%	87.2%	92.1%
100	85.7%	88.5%	94.8%

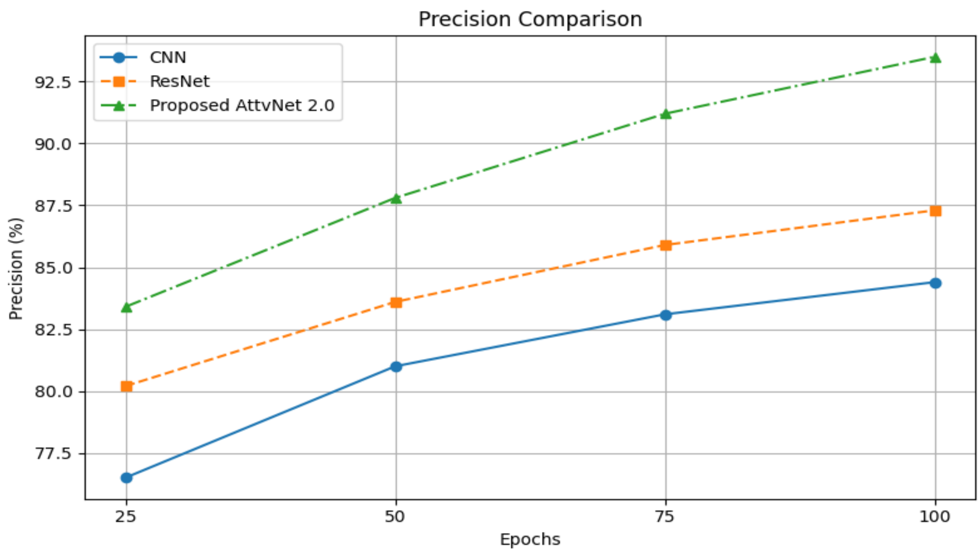

Figure 3: Precision Comparison

Table 8: Precision Comparison

Epochs	CNN	ResNet	Proposed AttvNet 2.0
25	76.5%	80.2%	83.4%
50	81.0%	83.6%	87.8%
75	83.1%	85.9%	91.2%
100	84.4%	87.3%	93.5%

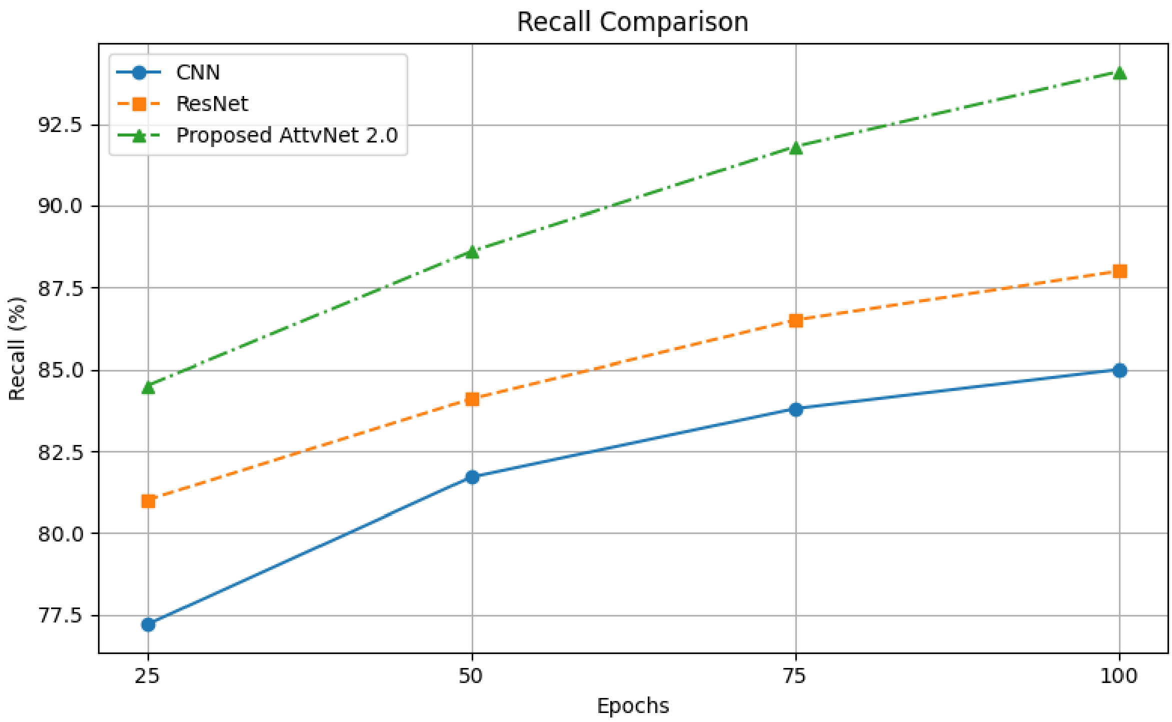

Figure 3: Recall Comparison

Table 9: Recall Comparison

Epochs	CNN	ResNet	Proposed AttvNet 2.0
25	77.2%	81.0%	84.5%
50	81.7%	84.1%	88.6%
75	83.8%	86.5%	91.8%
100	85.0%	88.0%	94.1%

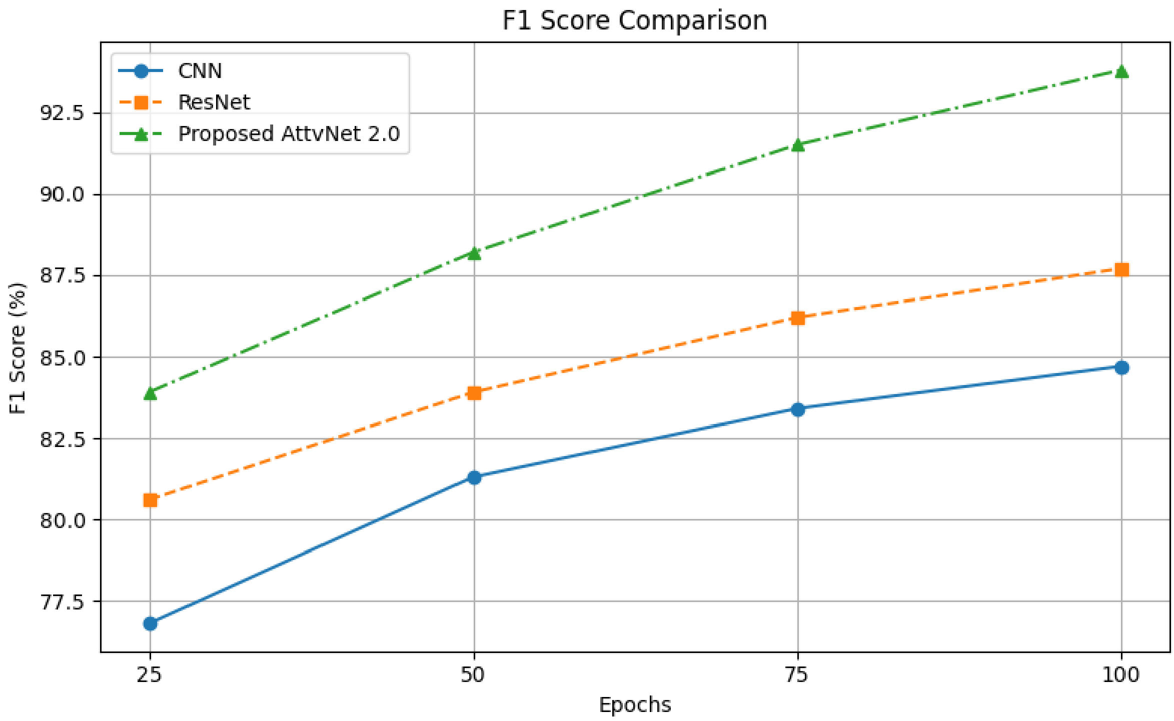

Figure 4: F1 Score Comparison

Table 10: F1 Score Comparison

Epochs	CNN	ResNet	Proposed AttvNet 2.0
25	76.8%	80.6%	83.9%
50	81.3%	83.9%	88.2%
75	83.4%	86.2%	91.5%
100	84.7%	87.7%	93.8%

The proposed AttvNet 2.0 model beats the methods now in use already in terms of accuracy, precision, recall, and F1 score. The proposed model reached 85.6% accuracy during the early training phase, which lasted 25 epochs. This is more accurate than CNN (78.2%) and ResNet (81.4%). The proposed model attained an accuracy of 89.3 percent after fifty epochs; CNN and ResNet, meanwhile, remained at 82.5% and 84.8%, respectively, over the same time period. Attention-based feature extraction and residual learning mechanism helped also the constant increase in precision and recall by enhancing the network's ability to capture fine details and patterns in the ultrasound images. Among several other techniques supporting this development is residual learning. AttvNet 2.0's accuracy was 94.8%, precision 93.5%, recall 94.1%, and F1 score 93.8% by the time 100 epochs had elapsed. This was a significant rise over CNN, which was 9%, and ResNet, which was approximately 6%. Residual learning ensured consistent gradient flow and improved feature propagation across the entire model; the attention mechanism let the model concentrate on regions with high diagnostic relevance. The model's steady increase in performance metrics indicates that it has been able to handle the challenges connected to speckle noise and small lesion detection in breast ultrasound images.

Conclusion

The proposed AttvNet 2.0 model outperforms CNN and ResNet models in early detection and speckle noise reduction in breast ultrasound images. By allowing the model focus on clinically relevant areas, the attention-based feature extraction mechanism increases both recall and accuracy. Residual learning promotes in-depth feature knowledge acquisition. Keeping gradient flow and improving convergence stability assist to accomplish this. The findings of the studies done over all training epochs reveal that AttvNet 2.0 is more accurate, precise, recall, and F1 score than the models now in use. Essential for breast cancer detection, the model has demonstrated its ability to reduce the number of false negatives and raise diagnostic dependability. Its steady increases in F1 score and recall demonstrate this. AttvNet 2.0's extraordinary capacity to detect speckle noise and complicated patterns implies it may be applied in actual clinical settings. Its capacity to maintain a high level of accuracy and recall ensures consistent classification and lowers misdiagnosis rates, so enabling it to be a helpful tool for enhancing breast cancer diagnosis outcomes. Its adaptability to variations in ultrasound image quality and lesion size increases the model's relevance in the domain of medical imaging technology even more.

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