A Novel Deep Learning Approach for Speckle Denoising Using Hyperparameter Tuning

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***Abstract*—Ultrasound imaging is one of the key noninvasive diagnostic methods used in medicine today. Many of the Deep Learning (DL) speckle denoising algorithms, in particular Autoencoder models and Convolutional Neural Network (CNN) based techniques, tend to be overfit, have low accuracy, or even perform badly on different sets of data. To help tackle these problems, the study proposed a new CNN architecture based model UNet-Elu that incorporates an Exponential Linear Unit (ELU) as its activation function. ELU is also used to endow the model with non-linearity while facilitating the flow of gradients within the model. The batch normalization and dropout layers are added with focus on improving accuracy and preventing overfitting. The proposed framework is evaluated in two stages. In stage 1 the proposed framework is compared with fine-tuned state-of-the-art UNet, UNet-ReLU, CNN Autoencoder and other filtering methods. For stage 2 comparative analysis transfer learning models are optimized and compared. The proposed framework performs without any sign of performance degradation and overfitting when tested on different datasets. This model was evaluated using the evaluation metrics of Peak Signal-to-Noise Ratio (PSNR), structural similarity (SSIM) and Mean Square Error (MSE) with different levels of speckle noise in order to determine the effectiveness of these techniques. It was able to achieve a PSNR of 37.76 dB and SSIM 98% for the UNet-Elu model which indicates a strong denoising performance. The optimized adjustment to the architecture and ELU activation function of the proposed model marks a significant improvement in ultrasound image denoising.**

***Keywords*—deep learning, speckle reduction, ultrasound imaging, denoising, improved framework**

I. Introduction

The most popular medical imaging technology that is crucial for medical diagnosis is ultrasound imaging. Due to limitations of medical technology, medical images are frequently obtained with low contrast, low intensity, noise, blurry, etc. These low-quality images are not suitable for diagnostic usage. As a result, precise image processing is required to create higher-quality images with more details for more insightful analysis. In ultrasound images, speckle noise is the main reason behind the degradation of images quality [1]. To obtain better quality images, this noise must be eliminated. US images seem noisy due to speckle noise, which can lead to diagnostic mistakes and a misidentification of disease changes in the body. Ultrasound imaging is used widely for a variety of reasons. It offers several benefits over computed tomography and magnetic resonance imaging, including cost-effectiveness, portability, and real-time operation. But the quality of the medical ultrasound images gets reduced by speckle noise. It diminishes the efficiency of human observation in distinguishing the subtleties of the diagnostic examination. Speckle noise [2] diminishes the contrast and brightness of the images, making it harder for radiologist to make an early diagnosis of disease. Various image processing methods [3] are often utilized, being the most commonly used methods are Median filtering, Wiener filtering, Anisotropic Diffusion, Non-local Means Denoising.

Deep learning-based image enhancement can successfully simulate complex nonlinear aberrations and noise, including ultrasonic speckle patterns, it shows promising results for image classification tasks with great application in the field of ultrasound image processing.Wang *et al.* [4] designed the unsupervised deep learning framework for speckle to noise suppression and completes its training process without using clean noise free images.

This approach reduces time, cost and efforts to manually annotating the reference images. It is still difficult to suppress the speckles while maintaining the structural boundaries because of the complex shape of speckles. Deep learning achieved the great success in image denoising using labeled and nonlinear process. Authors [5] proposed the transfer learning and hybrid Convolutional Neural Network (CNN) neural network a BAsNet is used to extract the structure boundaries before and after US image de-speckling. In this work [6], authors focus on developing a unique deep learning CNN based image filtering approach for improved clarity, and they present a deep learning classification model to recognize the noisy US images.

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The author's contributions in this research are as follows:

- Using many datasets, the newly developed enhanced framework for denoising speckle noise is created and assessed.
- The suggested design successfully attempts to prevent overfitting by selecting dropout layers, batch normalization, and max pooling at the appropriate stages.
- Design of hybrid model using transfer learning.
- Fine-tuning of the state-of-the-art transfer learning models for improved performance.
- Comparative analysis of proposed improved framework with transfer learning models for image enhancement.

The structure of the current paper is as follows: A rigorous literature review is given in Section II, and Section III explained the suggested methodology. A novel improved framework for ultrasound image denoising is proposed. Two different datasets are used for experimentation. Section IV is about result analysis of proposed framework, a validation of the model and an experimental assessment are given in this section. Section V presents the study's conclusion after a comparative analysis of the suggested procedure and concludes the study along with discussion for future work.

II. Literature Review

Different deep learning approaches for UI speckle noise reduction are discussed below. Authors [7] provides review on five different deep learning networks and suggested enhancement techniques of Ultrasound Images using U-Net Deep Learning CNN based model to improve resolution and minimize speckle noise in ultrasonography images. Instead of using an equal distribution, it evaluates at the impact of distributing noise levels at varied rates. Nahida [8] proposed U-Net Deep Learning network for reducing speckle noise in ultrasonography images. Gray scale, noisy ultrasound image dataset was used to train a model based on the U-Net architecture. Google Colab is used for the simulation & U-Shaped CNN approach implemented which proved that is a superior method for denoising images than auto encoder.

Li *et al.* [9] proposed 3D Deep learning algorithm for fast speckle noise reduction of breast ultrasound images. The spatial high-pass filtering method was used with logarithmic and exponential transformations to reduce over-sharpening and improve the characteristics of the glandular ultrasound imagine by targeted filtering. The suggested approach successfully reduces the speckle noise in breast ultrasonography images while maintaining edge information and sharply displaying image details. Authors [10] reviewed various deep learning methods, and applied ResNet method for speckle reduction. Finding suggested that ResNet architecture typically has highest performance than state of arts methods. For real-time ultrasound image despeckling, author [11] suggested a residual U-Net based on the mixed-attention mechanism (MARU). An encoder-decoder network is designed to extract features from noisy images and reconstruct despeckled ones. A lightweight mixed-attention block is introduced to enhance image details and reduce speckle noise during encoding.

Authors [12] developed an approach for image enhancement that improves overall quality, resolution, and noise suppression. To build US image augmentation datasets they used physics expertise that will improve the recommended method's training. This deep CNN model consists of 2 parts densely connected U-net type CNN and second resolution enhancement network. The present research [13] introduces a novel technique for noise reduction in ultrasound breast images named SMU (Srad Median Unsharp), which is necessary to obtain a Computer-Aided Diagnostic (CAD) for breast cancer. The performance of suggested methods of speckle reduction is demonstrated by a comparison of its findings with those of the other speckle noise reduction strategies. In order to smooth the speckle regions and improve the tissue structure in ultrasonic pictures, an adaptive image enhancement technique based on speckle detection and selective dynamic filtering is shown in [14]. Image quality improves when muscle borders and tissue structure are strengthened, and speckle areas are smoothed but not blurred. CNN's Deep Learning algorithm started to be applied to denoising problems in 2015. Shahdoosti [15] Introduced the CNN's single image Super-Resolution (SR) technique. Author [16] proposed deep learning-based approach for medical image fusion. The features used for the fusion weight computation model dictate DLMIF's performance. When the effectiveness of this classification networks was compared, it was found that the feature layers of the classification network could produce highly effective and desirable DLMIF outputs. Auto-encoder model [17] based on CNN network introduced for speckle noise reduction. In the last 10 years, Deep Learning (DL)-based fusion techniques have been increasingly popular and have been effectively applied in biomedicine [18] and computer image processing [19]. Many methods based on Deep Learning (DL) have also proven to offer distinct qualities and theories for fusing images. It is commonly known that Liu *et al.* [20] established the CNN-based fusion network, which was the first DL-based technique. To enhance ultrasound imaging of breast cancer, a deep learning technique called Auto-encoder with skip connection was employed [21]. It contrasted the outcomes using different filtering algorithms and Auto-encoder without using any skip connection techniques. The study found that a single auto encoder network produced better outcomes than traditional approaches while training images with 5 distinct noise levels. Authors used U-net CNN network for biomedical image segmentation [22]. To make greater use of the available annotated examples, they provide a network and training approach in this research that largely relies on data augmentation.

Authors [23] Presented FCNN-IDOA, a novel hybrid deep learning model that combines an optimization method and a Fundamental Convolutional Neural Network (FCNN). This FCNN model is based on Google Net framework, which has fifteen extra layers added to increase its expressiveness. In order to eliminate Speckle noise from US images of the breast and lung, Convolutional Neural Network Auto-Encoder (CNN-AE) [24] was developed. Author [25] provided five deep learning networks including Convolution Auto-encoder Denoising Network, Denoising U-Shaped Net, Batch Renormalization, Generative Adversarial Denoising Network and CNN Residual Network are used to reduce speckle noise in ultrasound images. Authors [26] had when compared to other deep learning techniques like convolutional neural networks, transfer learning breaks the curse of small datasets with its ease of use, efficiency, and cheap training costs. An in-depth examination is conducted, covering the following topics: (i) CNN's structure; (ii) transfer learning's background knowledge; (iii) the various strategies used in transfer learning; (iv) the use of transfer learning in medical image analysis's subfields; and (v) a discussion of the topic's potential in the future.

It has been observed in literature that the researchers are applying preprocessing, segmentation and augmentation in many studies to improve the model accuracy for ultrasound image denoising but still the results obtained by deep learning models have low validation and testing accuracy and suffer performance degradation and overfitting. Very few studies are carried out for reducing the trainable parameters. The datasets used in experiments are very limited in size, images lack uniformity in background. This study aims to reduce the gaps in literature by proposing the improved framework for speckle noise reduction and evaluating the proposed model through experiments using two different datasets.

III. Proposed Methodology

A. Proposed Improved Novel Framework for Ultrasound Image Denoising

For ultrasound image denoising proposed UNet-ELu model, a novel improved framework replaced ReLU activation function with Elu in UNet architecture. Exponential Linear Unit (ELU) in a U-Net is a promising approach that can potentially lead to improved performance. By adding non-linearity to the model, it enables the network to recognize and visualize complex patterns in the data. ReLU defined as $ReLU = f(x) = max(0, x)$ has a severe threshold at zero, but ELU offers a smooth curve for both positive and negative inputs [27]. In contrast to other activation functions, ELU has an additional alpha constant that ought to be greater than zero shown in Eq. (1). This activation function improves a model's accuracy and reduces the training time. It is mathematically represented as follows.

$$R(y) = \{y \quad y > 0 \\ \alpha.(e^{y} - 1) \quad y \le 0\} \tag{1}$$

where R (y) = y if y >0, and $\alpha.(e^{y} - 1)$ otherwise, where α is a positive constant. In order to address ReLU's deteriorating performance, we substituted ReLU with enhanced activation function is called Elu for it in the feature map. Similar to ReLU for positive inputs, outputting the input value directly for negative inputs, it approaches a negative value asymptotically. This provides a smoother gradient, which can help with optimization. It can be beneficial for deeper networks.

Here we used Conv 2D filter on images for feature extraction, Batch normalization, max pooling and Conv 2D transpose used for down sampling and up sampling resp. For better accuracy and performance, the improved optimized framework for ultrasound image denoising and enhancement is proposed by fusing the Unet_ELU model with CNN as depicted below in the Fig. 1.

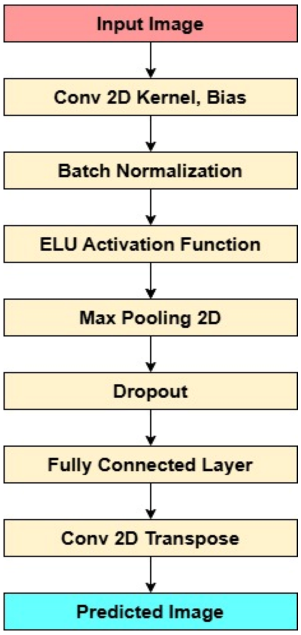


Fig. 1. Proposed improved UNet model architecture.

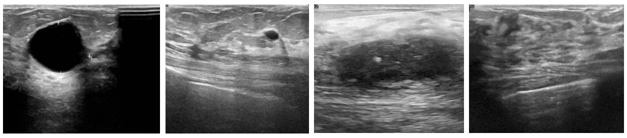
Here's a breakdown of the layers depicted in the image:

- Input Image: This is the layer where the data is fed into the network.
- Conv 2D Kernel, Bias: This layer applies a convolutional filter to the input image. Convolution is a mathematical operation that involves applying a filter to an image, producing a feature map that highlights specific features in the image.
- Batch Normalization: The activations of the preceding layer are normalized by this layer. Normalization assists in increasing the network's stability and training speed.
- ELU Activation function: This layer applies the ELU (exponential linear unit) activation function to the output of the previous layer. Activation functions introduce non-linearity into the network, allowing it to learn more complex patterns in the data.
- Max pooling 2D: This layer performs down-sampling on the data, reducing its dimensionality. This can help to reduce the computational cost of training the network and prevent over fitting.
- Dropout: This layer randomly drops a certain percentage of activations from the previous layer. This helps to prevent the network from over fitting to the training data.

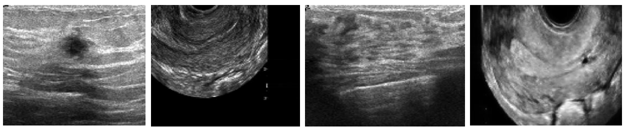
- Fully Connected Layer: This layer is a dense layer that connects all the neurons in the previous layer to all the neurons in the current layer. Fully connected layers are used to learn complex relationships between the features extracted by the convolutional layers.
- Conv 2D Transpose: This layer performs a deconvolutional operation. De-convolution can be used to upsample the data, increasing its dimensionality.
- Predicted Image: This is the output layer of the network. It produces the final image, which is the network's prediction.

B. Data Collection and Labeling

Two datasets of ultrasound images are used in this study. The Dataset1 is of 1520 Clear Ultrasound breast cancer Images where 437 benign, 210 malignant and 780 normal images. The images in the dataset1 are taken from publicaly available dataset of BUSI images from Kaggle. Dataset 2 is of 1435 abdominal images which are taken from Mendeley [23]. Data preprocessing perform on the images to make labeling of pred_origional images, noisy images, and images after adding noise on different variance level. In preprocessing process the images with size of 128×128 was used for training. The dataset is divided in 80% training and 20% testing sets. The sample dataset images are shown in Fig. 2.



(a)



(b)

Fig. 2. Sample data set of (a) BUSI images (b) Abdominal UI images.

C. Network Architecture

An encoder and a decoder are the two primary parts of the suggested model. Convolutional and pooling layers are used by the encoder to extract features, including noise, from the input image. The network starts with an input image of size 128×128×1 (a grayscale image). This novel design used 9 Convolutional layers, 1 dense layer and 1 dropout (fully connected) layer. The image is passed through a series of convolutional layers (represented by blue blocks) with increasing filter sizes and decreasing spatial dimensions. After each convolution layer, max pooling (represented in red arrows) is applied to reduce the spatial dimensions while retaining the most important features. The encoder network learn the complex features from the input, number of feature map increases (16,32,64,128,256) as we go deeper in the network.

In contrast, the decoder network starts by upsampling (represented with green arrow) takes the encoded image and reconstructs its features using a sequence of 2D transposed convolutional and concatenation layers. Skip connection (Black arrows) are an important feature of Unet, this helps in the recovery of fine grained information that are lost during downsampling. Convolution layers are used to refine the features and reconstruct the image. Detail network architecture diagram of proposed framework is shown in Fig. 3.

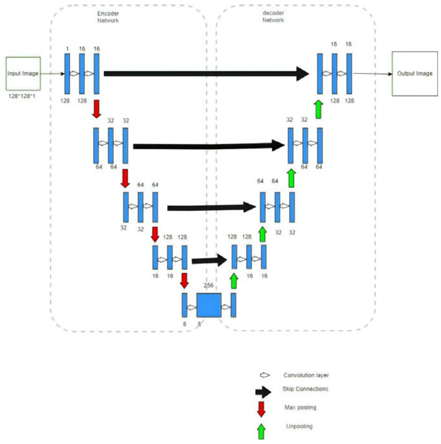


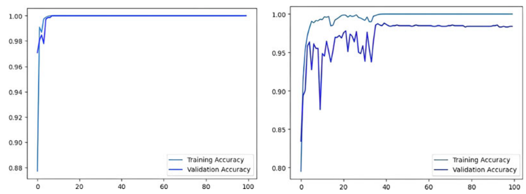
Fig. 3. Proposed model UNet-ELU layer architecture.

IV. Result and Discussion

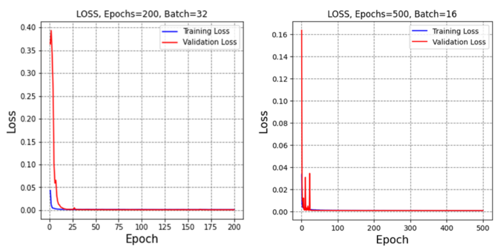
A. Performance Analysis for Training

After training the proposed improved model on a collected dataset using Adam optimizer with 0.001 learning rate, the accuracy and loss curve obtained is shown in the Fig. 4. It shows a smooth curve for the training and validation accuracy when trained for 500 and 200 epochs.Also, it shows best performance by achieving 100% training and validation accuracy after few epochs without any sign of performance deterioration when trained on both the datasets. Both the training loss and validation loss appear to be decreasing over the course of 500 & 200 epochs.

This suggests that the model is learning the patterns in the training data and generalizing well to unseen data. This is the significant result achieved by the proposed model.



(a)Accuracy Graph



(b) Loss Graphs

Fig. 4. Training performance of proposed framework of both dataset (a) Accuracy Graph (b) Loss Graph.

B. Comparison Architectural Design for Hybrid Improved Models

The Table I below explains the choice of design for the proposed model as well as for the other hybrid transfer learning models. Batch normalization is only applied to the proposed framework which has helped the model to improve its performance. 9 convolutional layers are added for the proposed improved network with varying sizes of dropout layers are used.

TABLE I. ARCHITECTURAL DESIGN OF PROPOSED IMPROVED MODEL COMPARED WITH OTHER DEEP LEARNING MODEL

Models	Convolu-tional Layer	Max Poolingapplied	Batch Normali-zation Applied	Drop Out	Dense
Proposed Framework (UNet-Elu)	9	Yes	yes	0.1,0.4	1
UNet-Relu	6	Yes	yes	0.1,0.2	1
UNet-Leaky Relu	3	Yes	No	0.2,0.3	2
CNN Autoencoder	2	yes padding	No	-	2

Table II clearly indicates the performance of the proposed framework using UNet-Elu is best as compared to optimized frameworks of UNet-Relu, Leaky-Relu and CNN Autoencoder. It achieves the highest accuracy of 98.54%. It also achieves the minimum loss. The proposed model, Leaky-Relu and UNet-Relu are heavier models having higher number of trainable parameters. Hence it is proved through experiments that the proposed framework is achieving the best performance and best selection choice for obtaining an improved and optimized model for noise denoising with highest accuracy.

TABLE II. TRAINING AND TESTING EXPERIMENTATION RESULTS

Models	Trainable Parameters	Training Accuracy%	Validation Accuracy %	Testing Accuracy%	TrainingLoss	Validation Loss
Proposed Framework (UNet_Elu)	7,157,234	98.99	97.45	98.54	6.43E-08	3.92E-05
UNet-Relu	2,177,649	97.16	91.66	91.16	0.1854	0.2345
UNet-Leaky Relu	1,700,519	96.04	96.99	95.68	0.1182	0.0993
CNN Autoencoder	1,669,825	92.26	89.45	90.32	0.45469	0.5786

C. Hyperparameter Tuning Optimization

When a learning algorithm is applied to any data collection, hyperparameter tuning is the process of determining a set of ideal hyperparameter values. The hyperparameter fine tuning has played an important role in improving the model accuracy of the proposed framework. The optimal set of hyperparameters is applied to the proposed framework after rigorous experimentation for obtaining the optimized framework and improved accuracy. By minimizing a predetermined loss function, that set of hyperparameters optimizes the model's performance and yields better, less error-prone outcomes.

The hyperparameter tuning is in the optimizer, loss function, learning rate, drop out layers and the number of epochs. Best set of hyperparameters for proposed framework mentioned below.

1. ADAM (Adaptive Moment Estimation) Optimizer used to minimize the loss function during the training of neural networks.
2. Learning rate is 0.001, was changed from 0.001 to 0.01.
3. No of batch size: 16,32,48, 64.
4. No of Epochs: 100, 200, 250, 500 highest epochs used to check increased accuracy and system performance.
5. Loss function: It shows better performance in proposed model shown in graph of validation and training loss.
6. For training dropout values 0.2, 0.3 and 0.4 were used to check accuracy. Best accuracy is achieved by hyperparamers of proposed models shows in Fig. 5.

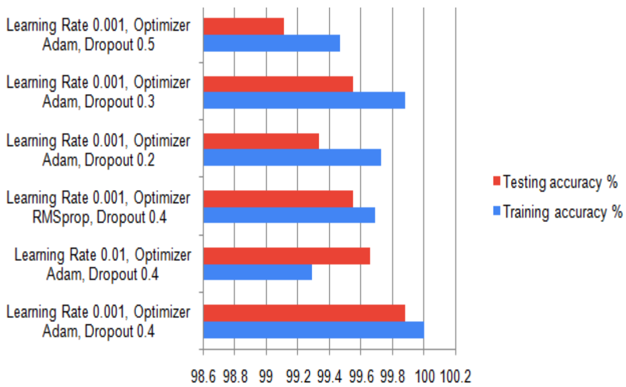


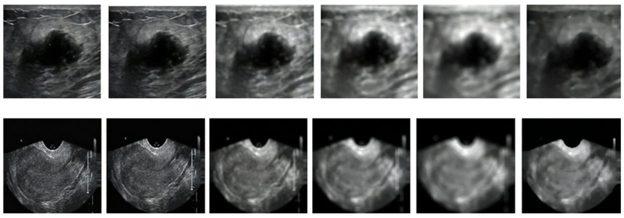
Fig. 5. Hyperparameter optimization for proposed framework.

The parameters were significantly reduced after applying convolution layer along with max pooling to the framework as compared to applying only dense layer. The proposed framework consisting of Elu activation function with 8 convolution layer, max pooling, batch normalization and a dense layer achieves the highest testing accuracy. Hence the above-mentioned Unet architecture design proves to be the best choice for obtaining improved and optimized framework for speckle noise reduction and better image enhancement.

D. Comparison of Proposed Framework with Hybrid Transfer Learning Models

Below are comparisons between the proposed model and different filtering techniques: In the results, you can see the Unet-Elu image's clarity exceeds than the other state of the arts filtering technique. Here I have used the training images to show the results the first image is UNet (Elu), which is improved and cleaner than the images produced by the other filtering techniques.

Comparative analysis of proposed UNet-Elu model with Gaussian filter, Average filter, Median filter and bilateral filter are given below in Fig. 6.



(a) (b) (c) (d) (e) (f)

Fig. 6. Comparison of different denoising techniques applied to the original image. (a) Original image; (b) Unet_Elu image; (c) gaussian filtering; (d) average filtering; (e) bilateral filtering; (f) median filtering.

To check the accuracy and generalization of proposed model. I have also used the validation dataset of 200 images each with dimension 128×128 pixels that is unseen images for the model. Speckle noise in these images is of multiplicative variance. These images were randomly selected from a dataset of breast cancer ultrasound scans acquired from publically available dataset. These validation dataset undergo with proposed model and finding of evaluation parameters are given below. Table III shows the results of 10 sample images from validation dataset with Peak Signal-to-Noise Ratio (PSNR), structural similarity (SSIM) and Mean Square Error (MSE) resp.

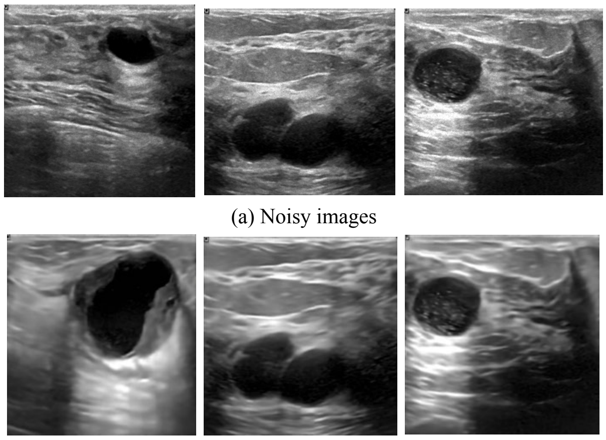
Table III shows that the suggested model performs well when using unseen imagess from the validation dataset, with highest PSNR value of 37.335 and SSIM 98% which very much similar to training dataset mentioned in the Table IV. MSE value is very much higher than training dataset here because the validation set having very dark images compared to trained dataset. Qualitative means visual presentation of validation dataset showing accuracy of the model given below in Fig. 7. Here the results indicate the clean images are more enhanced than noisy images mean the proposed model is learning well to unseen data also.

TABLE III. QUANTITATIVE RESULTS OF VALIDATION DATASET

PSNR	SSIM	MSE
36.870	0.981	3.349
36.740	0.973	3.773
37.262	0.953	2.215
37.024	0.980	2.904
35.361	0.978	4.485
36.296	0.976	5.627
37.335	0.988	2.462
35.222	0.979	2.328
36.417	0.980	1.785
36.916	0.978	3.228

TABLE IV. THE TABLE COMPARES THE PERFORMANCE OF EXISTING MODELS WITH PROPOSED MODEL

Denoising Methods	PSNR	SSIM	MSE
Proposed Novel model ((UNet-Elu)	37.766	98	0.0001
Leaky-Relu Model	32.243	90	0.002
UNet-Relu Model	29.125	93	0.001
CNN Autoencoder Model	28.79	85	0.001
Median blur filter	21.82	65	0.090
Gaussian Blur filter	21.98	71	0.092
Average Blur Filter	21.57	63	0.090
Bilateral Filter	20.83	55	0.089



(a) Noisy images

(b) Enhanced clean images of Unet-Elu Model

Fig. 7. Image denoising testing results of validation dataset.

The efficiency of the ultrasound image denoising was quantitatively evaluated using the following three widely used assessment measures: the Peak Signal-to-Noise Ratio (PSNR), structural similarity (SSIM) and Mean Square Error (MSE). The pixel by-pixel difference between the denoised image and the original noisy image measured by PSNR, SSIM assesses the similarity in terms of contrast, structure and brightness and MSE is the average square error between the maximum value of input image and reconstructed noise free images.

Three quantitative indicators are employed to assess the relative effectiveness of the proposed technique for speckle reduction compared to the alternatives. PSNR, MSE and SSIM are defined as given below:

1) Structural similarity index (SSIM):

It's a metric used to measure the similarity between two images.

$$SSIM(x,y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (2)$$

where μ_x and μ_y are the mean of denoised image x and original image y respectively; $\sigma\ xy$ is the covariance between x and y; σ_x and σ_y are the standard deviations of x and y, respectively; and c_1 and c_2 are constants.

2) Peak Signal to Noise Ratio (PSNR):

It is a quality measure between two images that gives a ratio of max power of a signal and the de-noised image given by Eq. (3).

$$PSNR = 10log_{10}(\frac{R2}{MSE}) \quad (3)$$

Here, Mean Square Error (MSE) and R stand for the greatest fluctuation of an input image. The quality of an original and a regenerated image is compared using this ratio.

3) Mean Square Error (MSE):

$$MSE = \frac{1}{mn} \sum_0^{m-1} \sum_0^{n-1} \| f(i,j) - g(i,j) \|^2 \quad (4)$$

Here, m×n represents the Size of image and f (I, j) ➔ Input image; g (I, j) ➔ Reconstructed noise free mage.

An image quality is determined by its Mean Square Error (MSE), where a lower number indicates a lesser error and thus a higher-quality image.

Comparative performance analysis of the proposed Unet-Elu model with other state-of-the-arts methods as shown in Table IV and Fig. 8.

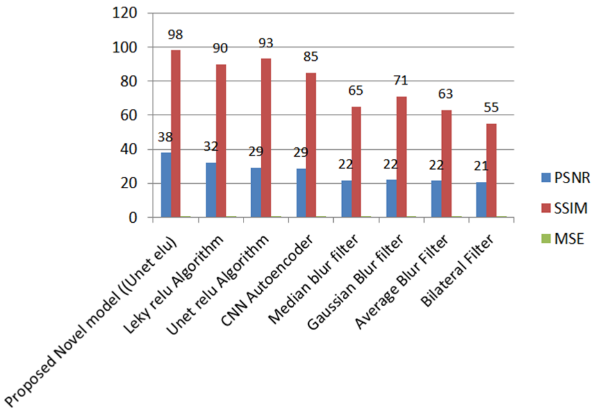


Fig. 8. Comparative analysis of proposed model with State-of-the-art models.

Autoencoder model [21] found that the PSNR value (28.37) and SSIM (92%) which is comparatively less than the proposed model. Higher PSNR and SSIM value and lower MSE value indicate good quality enhanced images. Above finding indicate that proposed framework has PSNR = 37.76, MSE is very low at 0.0001 and SSIM 98% shows that proposed framework achieves best result. Means proposed model has better image enhancement quality than the state of arts deep learning models.

V. Conclusion

Disease diagnosis relies heavily on ultrasound imaging. Speckle noise in ultrasonography images needs to be removed in order for physicians to make accurate disease diagnoses. It is seen in literature that the CNN based deep learning models used in the past for speckle noise reduction but they suffer performance degradation challenges. Some models give the better accuracy but supress the quality of images. In model training process mostly studies used 50 to 100 epochs to train the models. We have tested the model for 250 to 500 epochs on two distinct datasets; it showed no signs of overfitting or performance degradation, making it most suitable for use in US speckle reduction. Proposed model compared with CNN autoencoder, Unet-Relu Leaky-Relu and other filtering techniques. The results show that the proposed model produces the greatest PSNR values. The model's SSIM and PSNR values are, respectively 0.98 and 37.76 with 500 epochs. Testing revealed that the proposed model with optimization strategies gained the highest training and validation accuracy with the best results. The novel optimized framework using Unet-Elu activation with CNN layers to obtain an improved and optimized framework for ultrasound image enhancement with highest accuracy. Our future work will focus on the real life medical applications while continuously optimizing the performance of the model and I will analyze the effect of various parameters in concern with various medical images like Computed Tomography (CT), Magnetic Resonance Imaging (MRI) etc. Additionally developing lightweight optimization algorithm for contrast and resolution enhancement of Ultrasound images which could help to physicians for disease diagnosis.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

NP conducted the research and implementation of model. NP performs the experiment, calculation, analyzed the data and wrote the paper; VNP contributed to the final version of the manuscript and supervised the project. MMD guided in overall process, supervises the project in analysis, design and research publication. All authors discussed the results and contributed to the final manuscript.

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