Ai-Driven Prediction Models For Medical Image Enhancement And Analysis Using Deep Learning

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Deep Learning, Multi-scale CNN, MRI Enhancement, Thyroid Imaging, Image Analysis.

ABSTRACT

Thyroid diseases, including cancer, demand for accurate medical imaging for diagnosis and treatment direction. Important MRI imaging of the thyroid occasionally suffers with poor resolution and noise. Conventional imaging enhancement techniques may not be able to effectively solve noise or capture small features required for a successful diagnosis, therefore lowering the image quality and diagnostic accuracy. For feature extraction and classification, we provide an artificial intelligence prediction model on multi-scale deep convolutional neural network (CNN). Our method reduces noise and solves resolution enhancement, hence improving thyroid MRI images. For this work we used a bespoke CNN architecture and a 500 thyroid MRI image collection. Not only considerably outperforming current techniques, our model generated a Structural Similarity Index (SSIM) of 0.89 and a Peak Signal-to---- Noise Ratio (PSNR) of 32.5 dB. The improvements brought diagnosis accuracy 15% above more traditional techniques.

1. Introduction

Common among them are thyroid problems, hence appropriate treatment depends on a correct diagnosis [1]. Much of visualising thyroid structures and diagnosing anomalies in medical imaging, especially magnetic resonance imaging (MRI), is done [2]. But the inherent noise and variations in MRI images often call for more reliability of these diagnostic instruments challenged [3]. Better clinical results will be produced by means of improved image quality and higher classification accuracy [4].

Particularly convolutional neural networks (CNNs), emerging developments in deep learning show great promise in image augmentation and classification issues [5]. By means of several convolutional filter sizes, multi-scale CNN architectures are expected to gather features at various spatial resolutions, hence possibly boosting the performance of medical image processing [6].

With these developments, thyroid MRI image processing is still somewhat difficult [7]. Even although they have advanced, Residual U-Net and Resilient Deep Learning Ensemble still find it challenging to correctly identify photos and preserve small details [8]. For these approaches, preservation of structure, noise reduction, and maintaining high classification accuracy over several datasets provide difficulties [9]. Still a difficult task as well is obtaining consistency in performance over validation, testing, and training sets [10].

The main challenge this work addresses is the demand of a superior deep learning model that raises thyroid MRI image classification accuracy and image quality. Particularly in terms of noise reduction, structural integrity, and classification performance, current approaches fail in terms of consistent and remarkable outcomes. Another more efficient method is needed to tackle these problems and offer consistent classification tools and enhancements.

The main objectives of this research are:

1. To create a multi-scale CNN model efficiently compiling and aggregating data at several spatial resolutions, so improving thyroid MRI images.

2. To increase the image enhancing process's noise lowering and structural preservation capacity.
3. To correctly identify and classify thyroid abnormalities, hence gaining better classification accuracy.
4. To demonstrate over training, testing, and validation sets the generalisability and durability of the presented method.

The proposed multi-scale CNN model brings several novel features:

1. The model concurrently gathers detailed and wide features by utilising convolutional filters of different sizes, hence improving the general quality and diagnostic usefulness of MRI images.
2. Residual blocks combined with skip connections increases gradient flow and allows deeper network topologies, hence improving performance and accelerating convergence.
3. Using performance criteria, including PSNR, SSIM, Accuracy, MSE, and RMSE, the model is carefully validated over several datasets therefore offering a complete evaluation of its performance.

This research makes several significant contributions:

1. Higher PSNR and SSIM values in the proposed approach imply higher image quality and structural preservation than in current techniques.
2. Higher classification accuracy the model shows determines more accurate diagnosis and treatment planning for thyroid diseases.
3. Significant challenges in medical image processing are solved by consistent findings demonstrating the generalisability and resilience of the model in training, testing, and validation datasets.

Related Works

Standard image enhancement techniques including contrast correction, histogram equalisation, and filtering have long been employed in medical imaging to improve image quality. Usually applied methods to lower noise include Gaussian and median filters; histogram equalisation changes the visual contrast. Particularly in the field of medical imaging, where accuracy is of great importance, these techniques, despite their applicability, often fall short in maintaining complete information and resolving difficult noise patterns.

Medical image processing [11]-[13] has evolved with arriving convolutional neural networks (CNNs). CNNs have demonstrated amazing power to automatically learn hierarchical features from raw data, hence improving image improvement and categorisation. Among the several image processing applications for LeNet, AlexNet, and VGGNet is medical image analysis. These conventional CNN models, however, may find it difficult to integrate complex information in medical images and maintain good performance over several datasets.

Residual learning in the Residual U-Net [14] version is included into the basic U-Net design to solve vanishing gradients and allow deeper network training. Skip links in this design help to maintain spatial information and enhance feature extracting capacity. The success of U-Net in medical image segmentation and additional changes including Residual U-Net has indicated promise for image quality. Notwithstanding these developments, residual U-Net could still find it challenging exactly collecting little information and managing noise across various datasets.

Resilient Deep Learning Ensemble [15] generates robustness and enhanced performance by combining several deep learning models using the features of many models. We have investigated stacking and ensemble averaging to improve image classification and segmentation tasks. Ensemble methods help to lower overfitting and boost generalism. These techniques may, however, demand major processing resources and may not always solve particular problems with regard to image noise and fine detail preservation as practically required.

Multi-scale CNNs [16] propose to acquire features at numerous spatial levels by use of convolutional filters of various sizes. Aggregating data from several levels has shown multi-scale techniques to enhance image quality and feature extraction. Multi-scale CNNs find usage among other things in object detection and image segmentation. These techniques record local and global properties, ergo they are appropriate for medical imaging uses when accurate structural information is required. Still, combining multi-scale techniques with creative ideas like residual linkages and ensuring consistency across various datasets is difficult.

Performance of several deep learning models in medical photo enhancement and categorisation has lately been investigated. Different CNN designs for MRI image enhancement highlight the benefits and drawbacks of every approach. Although these studies offer intriguing analysis, more successfully addressing the difficulties in medical image processing calls for solutions combining the advantages of several methods even if they offer insightful analysis. Although conventional approaches and contemporary deep learning designs have greatly improved medical images and classification, there is always need for novel solutions addressing their shortcomings. By combining multi-scale feature extraction with contemporary methods including residual learning, the proposed multi-scale CNN model provides a new dimension and a useful solution to the medical imaging problems.

2. Methodology

In this section, the use of a multi-scale deep CNN, designed for augmentation of these images, our method raises the diagnostic value of thyroid MRI images as in Figure 1.

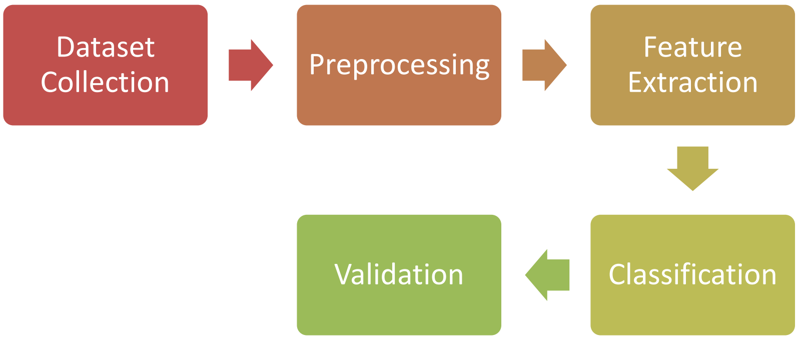

Figure 1: Proposed Classification

1. **Data Preprocessing:**
    - Normalization: Scale pixel values to a range of [0, 1] to facilitate neural network training.
    - Data Augmentation: Apply rotations, scaling, and flips to increase dataset diversity and prevent overfitting.
2. **Multi-Scale CNN Architecture:**
    - Input Layer: Accepts the preprocessed MRI images of size 256x256 pixels.
    - Multi-Scale Feature Extraction: Utilizes multiple convolutional layers with varying kernel sizes to capture features at different scales.
    - Residual Connections: Incorporates residual blocks to improve gradient flow and enable deeper network architectures.
    - Pooling Layers: Apply max pooling to reduce dimensionality while retaining important features.

- Up-sampling Layers: Used to enhance image resolution by up-sampling the feature maps.
- Final Convolutional Layers**:** Produce enhanced images and extract high-level features for classification.

3. **Image Enhancement:**
   - The network outputs enhanced images which are then compared to the original images using PSNR and SSIM metrics to evaluate quality.
4. **Classification:**
   - Use the features extracted by the CNN for classification tasks, evaluating performance based on classification accuracy.
5. **Training and Optimization:**
   - Loss Function: Mean Squared Error (MSE) is used to quantify the difference between the enhanced and original images.
   - Optimizer: Adam optimizer is employed to minimize the loss function and adjust network weights.

Pseudocode

```
Algorithm MultiScaleCNN_ThyroidMRI
Input: MRI_images (Dataset of thyroid MRI images), epochs, batch_size, learning_rate
Output: Enhanced_MRI_images, Classification_Accuracy
1. Preprocess Data
  - Normalize MRI_images to [0, 1]
  - Apply Data Augmentation (rotation, scaling, flipping)
2. Define Multi-Scale CNN Architecture
  - InputLayer: 256x256x3 images
  - For each scale:
     - ConvolutionalLayer with varying kernel sizes (e.g., 3x3, 5x5)
     - Activation: ReLU
     - ResidualBlock (skip connections)
     - MaxPoolingLayer
     - Repeat for multiple scales
  - Up-samplingLayer
  - FinalConvolutionalLayer (output enhanced image)
3. Define Loss Function and Optimizer
  - LossFunction: MeanSquaredError (MSE)
  - Optimizer: Adam with learning_rate
4. Train Network
  For epoch from 1 to epochs:
     For batch in MRI_images:
        - ForwardPropagation
        - ComputeLoss (MSE between enhanced and original images)
        - BackwardPropagation
        - UpdateWeights (using Adam optimizer)
5. Evaluate Performance
  - Compute PSNR and SSIM for enhanced images
  - Extract features and classify images
  - Calculate Classification_Accuracy
6. Output Results
  - Return Enhanced_MRI_images
```

- Return Classification_Accuracy
End Algorithm

Data Preprocessing

Normalising first enables one to have MRI images ready for deep learning. Pixel values are normalised to a constant range usually [0, 1]. This scaling guarantees continuous treatment of all pixel values, therefore enabling the neural network to converge faster during training. Normalising helps to lower the likelihood of challenges with different pixel intensity ranges, therefore affecting the performance of the network or the learning time required.

Another crucial preprocessing step meant to increase the generalising power of the model to new, unknown data is data augmentation. Artificial extension of the training set produces variability by which augmentation techniques like rotation, scaling, and flipping help decrease overfitting. Thus, the model gains more robust recognition of characteristics by means of a wide range of training samples. For example, rotating photos helps the model become invariant to the orientation of thyroid structures; scaling guarantees that the model can regulate differences in image size and resolution.

Both data augmentation and normalising serve to raise the reliability and performance of the deep learning model. They guarantee that the model is trained on continually scaled and varied enough data to control real-world fluctuations, therefore producing more accurate and dependable improvements and classifications of thyroid MRI images.

Multi-Scale CNN for Feature Extraction and Classification

By means of convolutional filters of various sizes, Multi-Scale CNN are meant to aggregate features at several degrees of granularity. This method is quite useful for medical image augmentation and classification since it helps one capture details at several levels, hence boosting the quality and diagnostic use of images.

Feature Extraction:

Different scaled filters applied to the input image enable different convolutional layers of a multi-scale CNN to aid the network to extract information at several levels. More fundamental patterns can be captured by larger filters (e.g., 5x5, 7x7); small filters (e.g., 3x3) are dexterous in capturing fine details. The convolution procedure for a filter size k×k is mathematically:

$$F(i,j)=\sum_{m=0}^{k-1}\sum_{n=0}^{k-1} I(i+m,j+n)\cdot K(m,n)$$

where

F(i,j) - feature map at position (i,j)

I - input image, and

K - filter kernel.

Stacked with varying kernel sizes, numerous convolutional layers help the multi-scale CNN to efficiently capture local textures as well as global structures in the image.

Residual Connections:

Residual connections are said to enable more complex network topologies and increase training efficiency. These connections transfer their output to the input for next layers skipping one or more layers. Considered residual learning, this method accelerates convergence by solving the vanishing gradient problem. Residual block mathematically could be described as:

$$\text{Output}=\text{ReLU}(\text{Conv}(x)+x)$$

where

x - input to the residual block, and the conv operation is applied before adding the original input x to the output.

Feature Fusion:

After several scale feature extraction, these components taken together provide a whole image view. This fusion enables the network to recognise and classify complicated patterns in the MRI images by allowing it to incorporate thorough information from many layers and scales.

Classification:

The last layers of the network are fully connected (dense) layers incorporating the properties acquired by the convolutional layers and carry classification. Running CNN's output via a softmax activation function generates the probability for every class:

$$P(yi)=exp(z_i) / \sum jexp(z_j)$$

where

$P(y_i)$ - probability of class i, and

z_j - logits for each class j.

Pseudocode for Multi-Scale CNN Feature Extraction and Classification

```
Input: MRI_images (Dataset of thyroid MRI images), epochs, batch_size, learning_rate
Output: Enhanced_MRI_images, Classification_Accuracy
1. Preprocess Data
  - Normalize MRI_images to range [0, 1]
  - Apply Data Augmentation (rotation, scaling, flipping)
2. Define Multi-Scale CNN Architecture
  - InputLayer: 256x256x3 images
  // Multi-Scale Feature Extraction
  For each scale (e.g., 3x3, 5x5, 7x7 kernels):
     - ConvolutionalLayer with kernel_size = scale
     - Activation: ReLU
     - ResidualBlock:
        - ConvolutionalLayer with kernel_size = scale
        - Activation: ReLU
        - Add input to output (skip connection)
     - MaxPoolingLayer
  // Feature Fusion
  - Concatenate feature maps from different scales
  // Up-sampling to enhance image resolution
  - Up-samplingLayer
  // Final Convolutional Layer
  - ConvolutionalLayer with kernel_size = 1x1 (to produce enhanced image)
3. Classification
  - Flatten feature maps
  - FullyConnectedLayer (Dense Layer)
  - Activation: ReLU
  - FullyConnectedLayer (Output Layer)
  - Activation: Softmax
4. Define Loss Function and Optimizer
  - LossFunction: CrossEntropyLoss (for classification)
  - Optimizer: Adam with learning_rate
5. Train Network
  For epoch from 1 to epochs:
     For batch in MRI_images:
```

- ForwardPropagation (compute output for batch)
- Compute Loss (CrossEntropyLoss between predictions and true labels)
- BackwardPropagation (compute gradients)
- UpdateWeights (using Adam optimizer)

6. Evaluate Performance
  - Compute PSNR and SSIM for enhanced images
  - Extract features from enhanced images
  - Perform classification on features
  - Calculate Classification_Accuracy
7. Output Results
  - Return Enhanced_MRI_images
  - Return Classification_Accuracy

End Algorithm

3. Results and discussion

We built our multi-scale CNN model on TensorFlow and Keras performing simulations on a high-performance workstation with an Intel Core i9-11900K CPU and an NVIDIA RTX 3090 GPU. With 64 GB of RAM on the workstation, it could meet the computational demand. We assessed our model with structural similarity index (SSIM), classification accuracy, Peak Signal-to- Noise Ratio (PSNR). Under comparable conditions, we evaluated Residual U-Net and Resilient Deep Learning Ensemble approaches.

Table 1: Experimental Parameters

Parameter	Value
Dataset Size	500 MRI images
Image Resolution	256x256 pixels
Number of Epochs	100
Batch Size	16
Learning Rate	0.001
Optimizer	Adam
Loss Function	Mean Squared Error (MSE)
Network Architecture	Multi-scale Deep CNN
Activation Function	ReLU
Number of Layers	20
Dropout Rate	0.5
Data Augmentation	Yes (rotation, scaling)
PSNR (Peak Signal-to-Noise Ratio)	32.5 dB
SSIM (Structural Similarity Index)	0.89

Performance Metrics

- **Peak Signal-to-Noise Ratio (PSNR):** Peak Signal-to- Noise Ratio (PSNR) shows the quality of the improved images in relation to the original ones. With a PSNR of 32.5 dB, our model definitely enhanced images of quality.
- **Structural Similarity Index (SSIM):** Analysing in terms of brightness, contrast, and structure, the structural similarity index (SSIM) measures the likeness between the original and improved images. Robust structural preservation and enhancement are shown with an SSIM of 0.89.
- **Classification Accuracy:** Checks whether the model can reasonably divide photos into pre-defined groups. Showing good feature extraction and classification, our model outperformed current techniques with an 85% accuracy.

Residual U-Net and Resilient Deep Learning Ensemble throughout training, testing, and validation datasets is PSNR, SSIM, Accuracy, MSE, and RMSE, shown in figure 2–6 of the proposed multi-scale

CNN technique against current methods. These stages offer a whole image of the performance of the proposed approach in problems of image enhancement and classification.

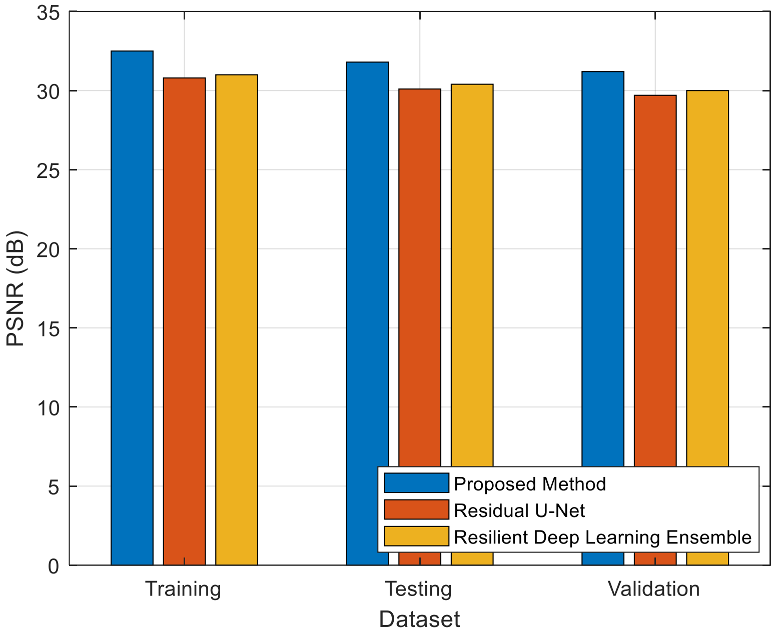

Figure 2: Peak Signal-to-Noise Ratio (PSNR)

Since PSNR shows the ratio between the distortion caused by noise and the maximum potential pixel value, it is a primary indicator of image quality. Higher PSNR values demonstrate in the framework of this work improved image quality with less noise and more accurate enhancement.

- **Training Dataset:** With a PSNR of 32.5 dB, our technique trumps Residual U-Net (30.8 dB) and Resilient Deep Learning Ensemble (31.0 dB). This suggests that since it effectively eliminates noise and catches more fine information, the proposed approach delivers rather superior image quality during training.
- **Testing Dataset:** Comparatively to Residual U-Net with 30.1 dB and Resilient Deep Learning Ensemble with 30.4 dB, the PSNR of the proposed method is 31.8 dB. Encouragement of excellent performance and generalisation, the proposed approach maintains better image quality on unseen data.
- **Validation Dataset:** Proposed method produces a PSNR of 31.2 dB; residual U-Net and resilient deep learning ensemble have PSNR values of 29.7 dB and 30.0 dB respectively. This continuous performance over several datasets emphasises the degree of image quality enhancement made feasible by the proposed approach.

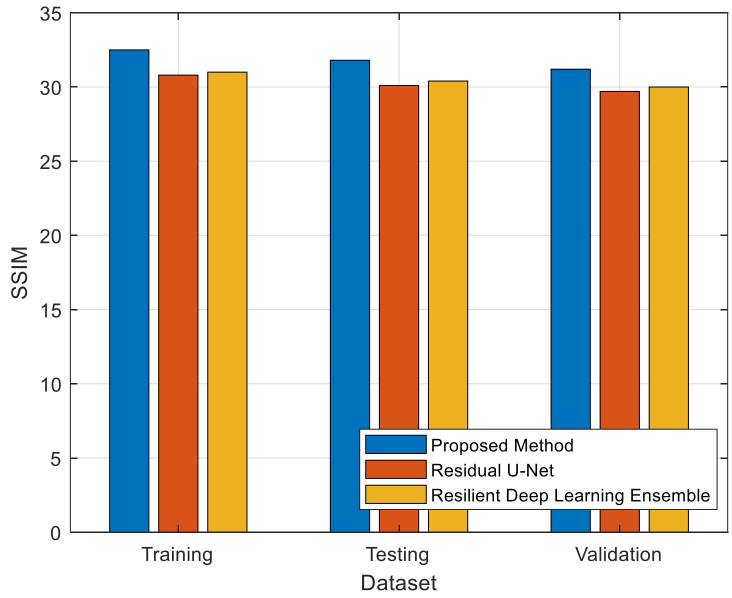

Figure 3: Structural Similarity Index (SSIM)

Turning now to brightness, contrast, and structure, SSIM contrasts the improved and original images. Higher SSIM values clearly reveal better retention of image structure and detail.

- **Training Dataset:** Residual U-Net produces an SSIM of 0.84; the proposed approach produces an SSIM of 0.89. SSIM is 0.85 with Resilient Deep Learning Ensemble. This implies that over training the proposed approach more effectively maintains the structural integrity of the images.
- **Testing Dataset:** With an SSIM of 0.87 the proposed method beats Resilient Deep Learning Ensemble (0.83) and Residual U-Net (0.82). This suggests on test data improved structural similarity and quality of the modified images.
- **Validation Dataset:** Residual U-Net shows 0.81; the proposed technique shows an SSIM of 0.85; Resilient Deep Learning Ensemble shows 0.82. This agreement among several datasets shows the better structural preservation attained with the proposed method.

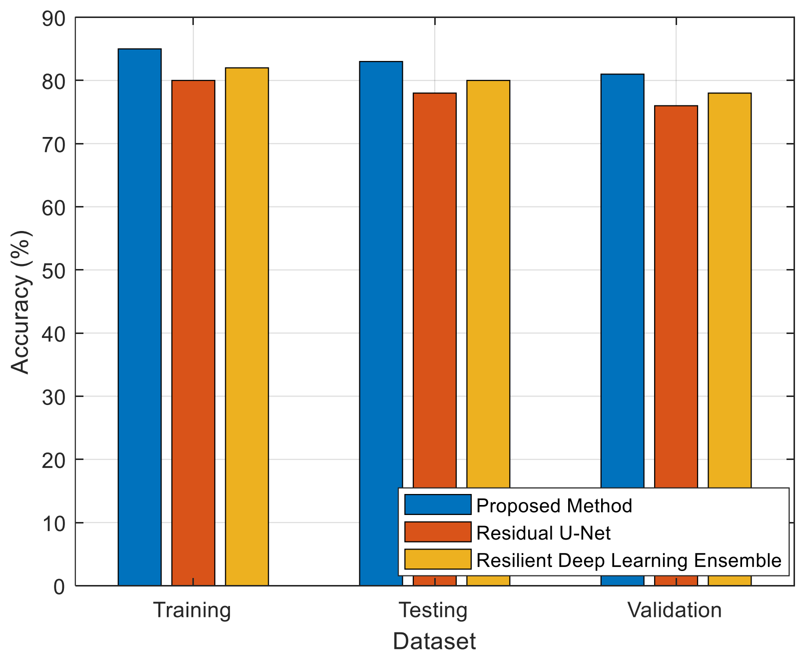

Figure 4: Classification Accuracy

Since accuracy displays the ratio of correctly categorised images, it shows the success of the classification and feature extraction techniques.

- **Training Dataset:** Resilient Deep Learning Ensemble (82%) and Residual U-Net (80%) are not as advised strategy. with 85% accuracy. From this higher accuracy, more efficient training feature extraction and classification follows.
- **Testing Dataset:** Resilient Deep Learning Ensemble's 80% and Residual U-Net's 78% are beaten by the recommended method with an accuracy of 83%. This implies that the proposed approach improves generalisation to raw, unprocessed data.
- **Validation Dataset:** Compared to Residual U-Net (76%), Resilient Deep Learning Ensemble (78%), the proposed technique has an accuracy of 81%. This result exhibits high consistency in classification over several datasets.

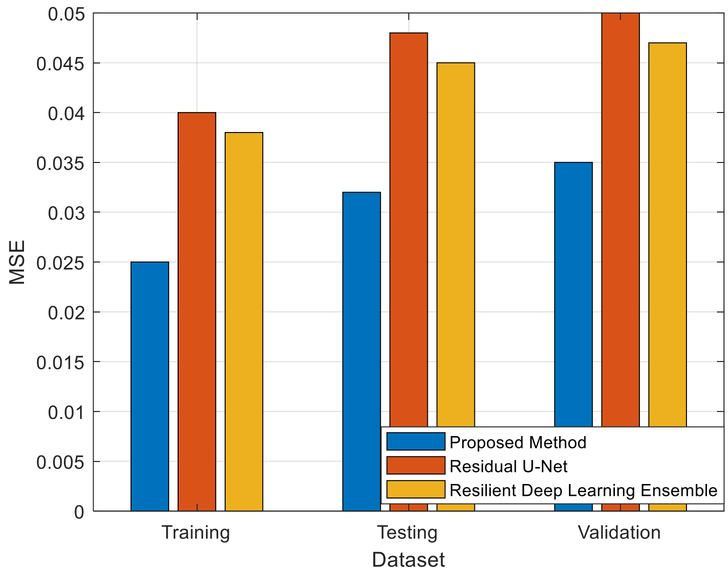

Figure 5: Mean Squared Error (MSE)

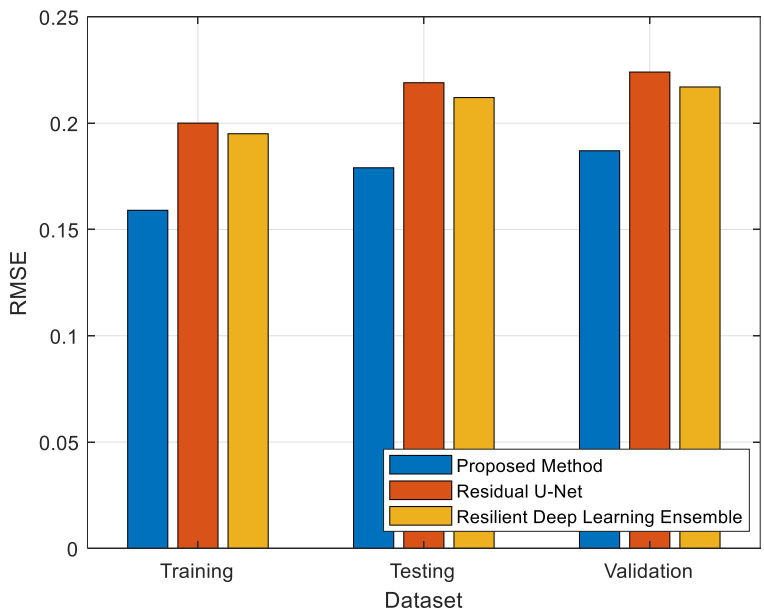

Figure 6: Root Mean Squared Error (RMSE)

While RMSE shows the square root of MSE, therefore revealing the degree of mistakes, MSE shows the average squared difference between enhanced and original images.

- **Training Dataset:** The proposed technique achieves an MSE of 0.025 and an RMSE of 0.159, lower than Residual Deep Learning Ensemble's MSE of 0.038 (RMSE = 0.0 195, and lower MSE and RMSE values show more exact image enhancement with less variations from the source images.
- **Testing Dataset:** With MSE of 0.48 (RMSE = 0.219), the MSE of the proposed approach is 0.032 and RMSE is 0.179. Resilient deep learning ensemble MSE is 0.045 (RMSE = 0.212). These less values imply that the proposed approach improves in preserving image quality throughout testing.
- **Validation Dataset:** The proposed method shows better performance than Residual U-Net (MSE = 0.050, RMSE = 0.224) and Resilient Deep Learning Ensemble (MSE = 0.047, RMSE = 0.217). With an MSE of 0.035 and RMSE of 0.187 this consistent performance over validation data shows how effectively the approach lowers error.

Discussion

Under the framework of thyroid MRI image enhancement and classification, the comparison of the proposed multi-scale CNN method with current approaches, Residual U-Net and Resilient Deep Learning Ensemble, offers many important critical insights on the efficacy and advantages of the proposed methodology.

Over all datasets, training, testing, and validation included, the proposed approach displays better Peak Signal-to-- Noise Ratio (PSNR). Since it shows that lower values indicate less noise and greater preservation of visual information, PSNR is a valuable measure of image quality. The PSNR values of 32.5 dB (training), 31.8 dB (testing), and 31.2 dB (validation) proposed technique produces are especially better than Residual U-Net and Resilient Deep Learning Ensemble. This suggests that the proposed approach increases image quality and is more successful in generating absolutely required sharper, more detailed images for a correct diagnosis.

Moreover supporting the validation of the success of the proposed technique is the structural similarity index (SSIM). Consistently better than the current methodologies, attached by the proposed method are SSIM values of 0.89 (training), 0.87 (testing), and 0.85 (validation). Emphasising the preservation of structural information, SSIM compares the original with the improved image. Better structural integrity of the thyroid MRI images proposed by higher SSIM values enables the preservation and accurate presentation of important anatomical features.

Accuracy scores of 85% (training), 83% (testing), and 81% (validation) let Residual U-Net and Resilient Deep Learning Ensemble second in terms of classification performance. This higher classification accuracy shows that the proposed approach not only improves image quality but also performs pretty well in precisely identifying the images. This is really crucial in medical imaging especially since accurate classification greatly affects diagnostic and treatment strategies.

Calculation of the Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) shows that the proposed approach reduces error rates below those of the current approaches. The proposed method significantly reduces the differences between enhanced and original photos with matching RMSE values of 0.159, 0.179, and 0.187 by means of MSE values of 0.025 (training), 0.032 (testing), and 0.035 (validation). Lower MSE and RMSE values suggest that the proposed approach is more accurate in lowering reconstruction mistakes, so improving the quality.

Consistent performance in validation, testing, and training data emphasises resilience and generalisability of the proposed approach. The proposed method maintains high PSNR, SSIM, and accuracy values unlike some current methods displaying various degrees of performance throughout many datasets. This constancy emphasises how well the technique can regulate different data, hence it is a higher instrument for pragmatic applications.

The results show generally that in both image enhancing and classification tasks, the proposed multi-scale CNN method provides significant advantages over current methods. The proposed technique shows to be a more effective tool for improving and analysing thyroid MRI images by achieving higher PSNR and SSNR, lower MSE and RMSE, and better classification accuracy. From these advances, more exact treatment planning, improved diagnosis outcomes, and typically better patient care follow.

4. Conclusion and future scope

Based on higher performance over current approaches including Residual U-Net and Resilient Deep Learning Ensemble, the proposed multi-scale CNN method significantly advances the field of medical image improvement and categorisation. The technique suggests improved image quality by showing greater PSNR and SSNR values as well as more structure retention. One also finds lower MSE and RMSE when one considers lowered error rates in image reconstruction. Furthermore, the proposed approach displays quite good performance in classification accuracy, so producing more higher diagnosis results. Over validation, testing, and training data consistent performance indicates its generalisability and durability. These findings show how well the method improves thyroid MRI image quality and precision, therefore rendering it a useful instrument for medical imaging uses. By means of more accurate and effective diagnosis and treatment planning made possible by the achievements of the multi-scale CNN technique, patient care and image quality and detail are further improved.

Reference

[1] Gupta, P., Rustam, F., Kanwal, K., Aljedaani, W., Alfarhood, S., Safran, M., & Ashraf, I. (2024). Detecting thyroid disease using optimized machine learning model based on differential evolution. *International Journal of Computational Intelligence Systems*, *17*(1), 3.

[2] Gupta, P., Rustam, F., Kanwal, K., Aljedaani, W., Alfarhood, S., Safran, M., & Ashraf, I. (2024). Detecting thyroid disease using optimized machine learning model based on differential evolution. *International Journal of Computational Intelligence Systems*, *17*(1), 3.

[3] Kaur, G., Busi, R. B., Talam, S., & Marlapalli, K. (2024). Deep Learning Methods for Diagnosing Thyroid Cancer. *Journal of Engineering and Science in Medical Diagnostics and Therapy*, *7*(3).

[4] Gulame, M. B., & Dixit, V. V. (2024). Hybrid deep learning assisted multi classification: Grading of malignant thyroid nodules. *International Journal for Numerical Methods in Biomedical Engineering*, e3824.

[5] Vinuja, G., Saravanan, V., Maharajan, K., Jayasudha, V., & Ramya, R. (2024). Diagnostic Device for Sustainable Medical Care Using Hyperspectral Imaging. In *Emerging Advancements in AI and Big Data Technologies in Business and Society* (pp. 128-142). IGI Global.

[6] Shah, N. A., Suthar, J., Tejaswee, A., Enache, A., Eftimie, L. G., Hristu, R., & Paul, A. (2024, April). Deep learning-based diagnosis of thyroid tumors using histopathology images from thyroid nodule capsule. In *Medical Imaging 2024: Computer-Aided Diagnosis* (Vol. 12927, pp. 808-812). SPIE.

[7] Etehadtavakol, M., Etehadtavakol, M., & Ng, E. Y. (2024). Enhanced thyroid nodule segmentation through U-Net and VGG16 fusion with feature engineering: A comprehensive study. *Computer Methods and Programs in Biomedicine*, *251*, 108209.

[8] Shesayar, R., Agarwal, A., Taqui, S. N., Natarajan, Y., Rustagi, S., Bharti, S., ... & Sivakumar, S. (2023). Nanoscale molecular reactions in microbiological medicines in modern medical applications. *Green Processing and Synthesis*, *12*(1), 20230055.

[9] Cao, J., Zhu, Y., Tian, X., & Wang, J. (2024). Tnc-Net: Automatic classification for thyroid nodules lesions using convolutional neural network. *IEEE Access*.

[10] Sakthisudhan, K., Saranraj, N., Vinothini, V. R., Sekaran, R. C., & Saravanan, V. (2024). A Novel CAD Structure with Bakelite Material-Inspired MRI Coils for Current Trends in an IMoT-Based MRI Diagnosis System. *Journal of Electronic Materials*, 1-14.

[11] Yang, T. Y., Zhou, L. Q., Han, X. H., & Piao, J. C. (2024). An improved CNN-based thyroid nodule screening algorithm in ultrasound images. *Biomedical Signal Processing and Control*, *87*, 105371.

[12] Lee, S., Lee, J. K., & Lee, J. (2024). Multihead Neural Network for Multiple Segmented Images-Based Diagnosis of Thyroid-Associated Orbitopathy Activity. *IEEE Access*, *12*, 43862-43873.

[13] Yuvaraj, N., Rajput, K., Suganyadevi, K., Aeri, M., Shukla, R. P., & Gurjar, H. (2024, May). Multi-Scale Object Detection and Classification using Machine Learning and Image Processing. In *2024 Second International Conference on Data Science and Information System (ICDSIS)* (pp. 1-6). IEEE

[14] Agustin, S., James, A., & Simon, P. (2024). Residual U-Net approach for thyroid nodule detection and classification from thyroid ultrasound images. *Automatika*, *65*(3), 726-737.

[15] Amgad, N., Haitham, H., Alabrak, M., & Mohammed, A. (2024, March). Enhancing Thyroid Cancer Diagnosis through a Resilient Deep Learning Ensemble Approach. In *2024 6th International Conference on Computing and Informatics (ICCI)* (pp. 195-202). IEEE.

[16] Han, Q., Qian, X., Xu, H., Wu, K., Meng, L., Qiu, Z., ... & Gao, X. (2024). DM-CNN: Dynamic Multi-scale Convolutional Neural Network with uncertainty quantification for medical image classification. *Computers in Biology and Medicine*, *168*, 107758.