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A proposed Wavelet-Neural Network Based Image Restoration

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Abstract The essential process of collecting raw data called image reconstruction which can interpret and analyze several imaging modalities in order to form an understandable image format for humans. Thus, the goal of image reconstruction is to create a usable image with high quality allowing the inspection of internal for defects without damaging the item. It consists of several cascade process like, data acquisition, preprocessing, and the application of a reconstruction algorithm and post-processing to enhance its visual quality. This paper proposed an algorithm of combining wavelet transform with neural network for image reconstruction. Such combination offers several significant advantages by leveraging the strengths of both techniques. The proposed hybrid algorithm is very effective in several tasks like image super-resolution, denoising, and medical imaging reconstruction. The algorithm depends on an 8-level wavelet decomposition for feature extraction and Elman recurrent neural network for uncompleted image in small and big losing blocks. The reconstruction achieved 100% of accuracy even with a losing case of 75% from the original image.

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Keywords: *Discrete wavelet Transform; Elamn Recurrrent; Neural Network; Feature Extraction.*

1. INTRODUCTION

The **Wavelet Transform** (WT) decomposes an image into different frequency components (sub-bands). This provides a multi-resolution representation, separating the coarse, low-frequency information from the fine, high-frequency details (like edges and textures). This decomposition makes it easier for the neural network to focus on specific features. For example, a network can be trained to handle noise in the high-frequency sub-bands while preserving important structural information in the low-frequency sub-bands [1]-[23].

Neural networks can often produce a higher quality reconstructed image with fewer artifacts and less blurring compared to conventional methods. They are adept at learning complex, non-linear relationships within image data, which allows them to effectively remove noise and fill in missing information while preserving fine details and structures [24]-[46].

Image Reconstruction using wavelet decomposition Feature Extraction with Recurrent Neural Network: The idea of combing neural networks with multiscale wavelet decomposition has been proposed by a number of authors.

The idea proposed here is based on discusses the main contribution of the proposed algorithm namely the novel combination of the feature extraction capability of wavelets. With dynamic classification properties of recurrent neural networks this combination is called wavelet network. Experimental analysis of the discriminatory power of the new proposed. It's using an Elman recurrent neural network (ERNW), or, if necessary, an ensemble of such networks, to detect and classify process event through the recognition of the reconstruction generated in a set of texture image. The Elman has one output for each considered event class, and 25 input streams for each texture image. The inputs are the consecutive value of feature extracted by „db4" wavelet decomposition.

The advantageous of the proposed hybrid image reconstruction are:

1- WT usually decomposes the signal into several low and high frequency bands which leads to multi-resolution analysis and feature localization.

2- Reduces computational complexity in comparison with Deep learning and Vision Transformers (ViTs) which have very high computational complexity. This makes the overall process more efficient without sacrificing quality.

3- It works on the wavelet coefficients rather than the raw pixel data which leads into enhanced performance.

4- It results into inherent sparsity since many of WT are close to zero. This not only speeds up the learning process but also leads to a more compact and efficient model.

2. NEURAL NETWORKS

S Neural networks offer several advantages for image reconstruction, a process that involves recovering an original

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image from incomplete, corrupted, or noisy data. Instead of relying on traditional, handcrafted algorithms, neural networks, particularly Convolutional Neural Networks (CNNs), can learn to perform this task directly from large datasets.

Traditional deep learning models, especially Vision Transformers (ViTs), can have quadratic computational complexity, making them expensive to use for high-resolution images. By applying the wavelet transform first, you can process the image at a lower resolution or in different sub-bands, which significantly reduces the computational burden on the neural network. This makes the overall process more efficient without sacrificing quality [24]-[46].

3. One-Dimensional and Two-Dimensional Wavelet Transforms

Wavelet transform is a transform whose basic function are shifted and expanded versions of themselves. The wavelet transforms break an image down into four sub- sampled, or decimated, images. In this study the field of texture analysis using wavelet transform will be examined for the reconstruction task. This transform is typically implemented in the spatial domain by using one-dimensional convolution filters. The *convolution theorem* states that convolution in the spatial domain is the equivalent of multiplication in the frequency domain. A particular set of wavelets is specified by a

particular set of number, called wavelet filter coefficients. Here, will largely restrict to wavelet filters in a class computed by the following references [3]- [23].

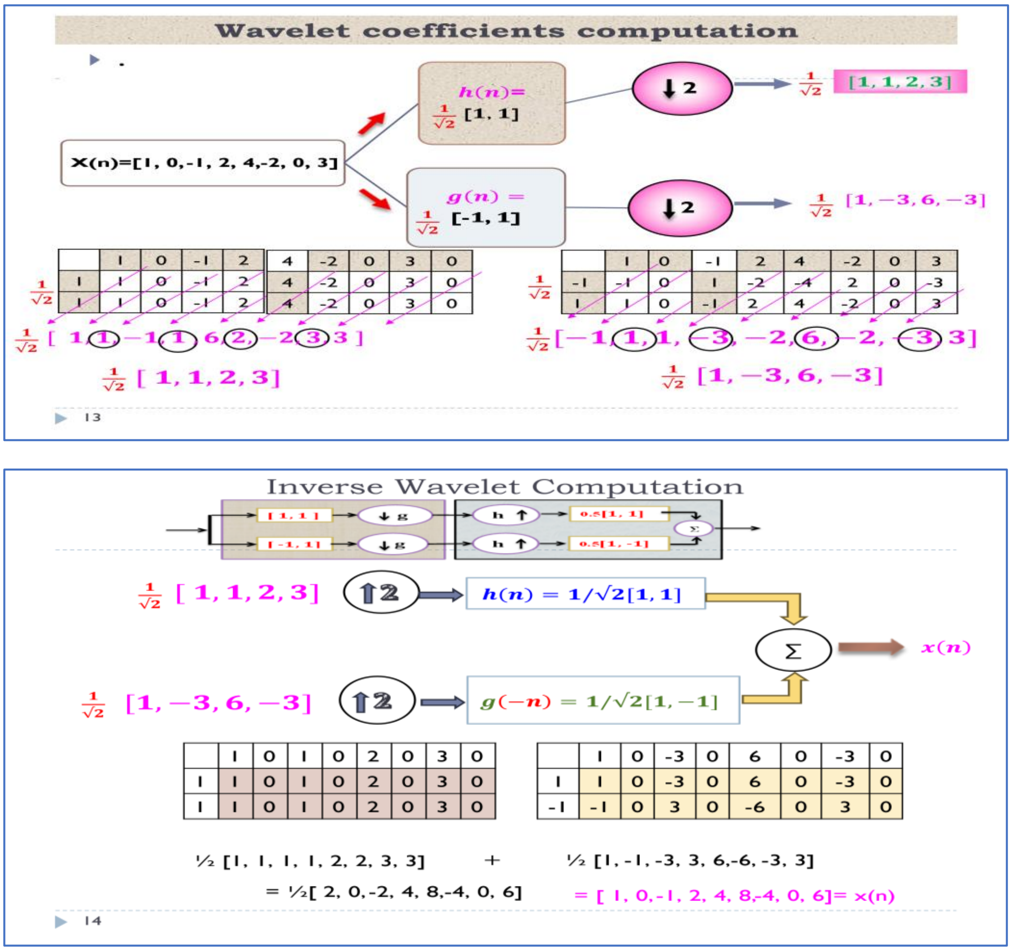

***Fig. 1**: Computation of one-Dimensional Wavelet Transform and bits inverse.*

Fig 1. gives the detail computations of wavelet transform coefficients as well as its inverse coefficients using the linear convolution techniques. Given the signal of one-dimension $x = [1, 0, -1, 2, 4, 8, -4, 0, 6]$, the two filters high and low will convolved linearly with the input signal first. Next the decimation by two will be applied to the output of the linear convolution. Finally the output wavelet coefficients will be of two parts, namely the low and high frequency parts respectively:

$$\frac{1}{\sqrt{2}}[1,\ 1,\ 2,\ 3] \qquad \frac{1}{\sqrt{2}}[1,\ -3,\ 6,\ -3]$$

In the inverse computation procedure these L and H wavelet Coefficients will be interpolated by 2 and then each of them will be forwarded to the linear convolution process. Finally, the

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outputs will be added to return the signal coefficients. The direct matrix multiplication of computation these coefficients are given in Fig. 2 below.

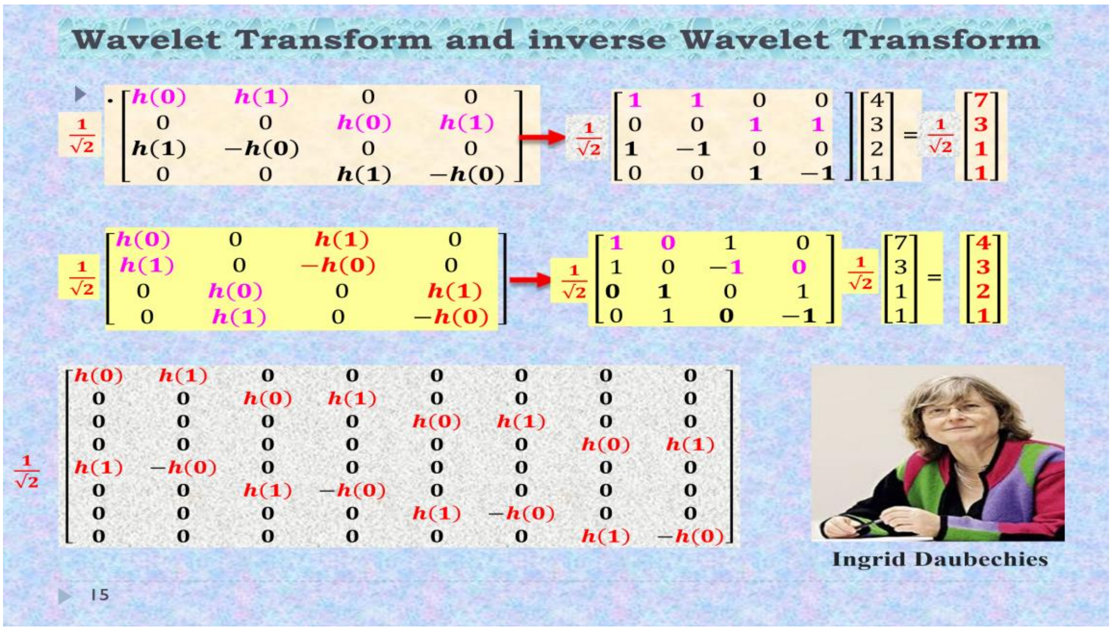
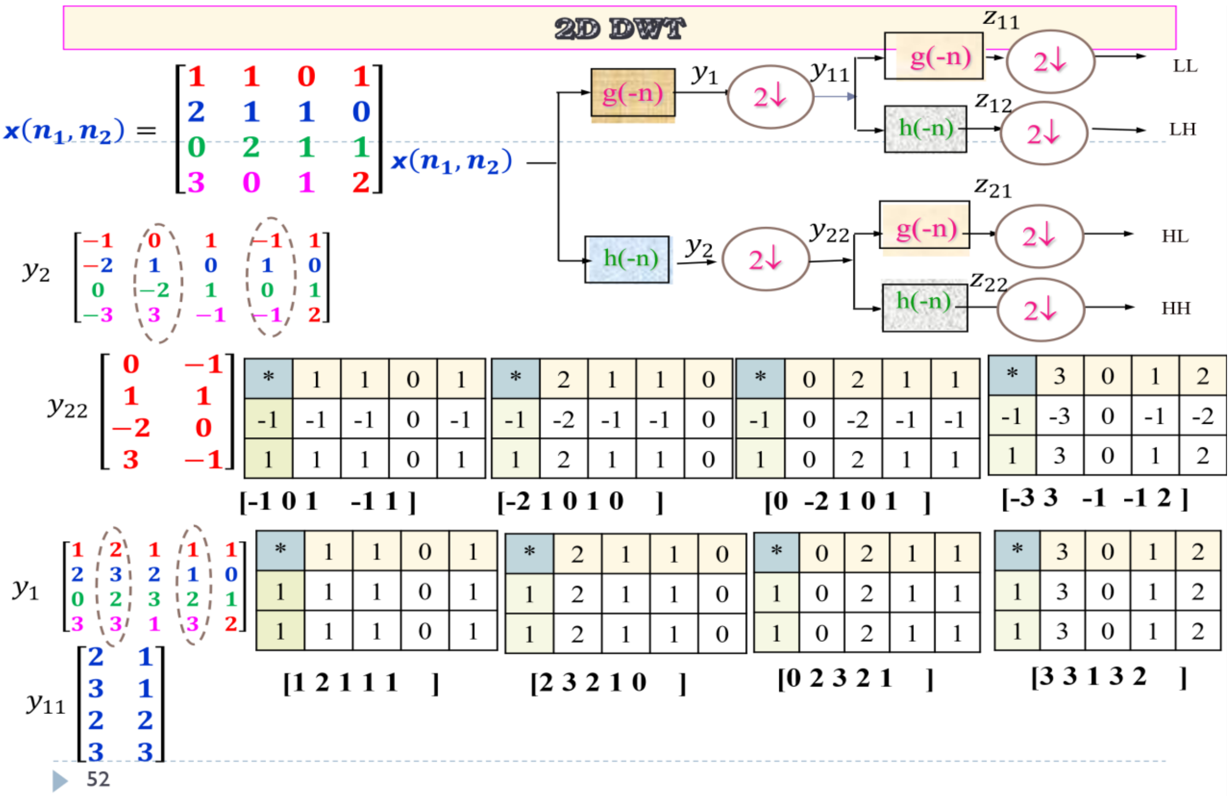


Fig. 2: *Direct matrix multiplication of computing wavelet Coefficients and their inverse*

The computations of the two-dimensional wavelet coefficients will be given next. The first wavelet transform operates in horizontal direction and the second wavelet transform operates in vertical direction [3]-[23]. A one level of two-dimensional wavelet decomposition and reconstruction are depicted in figure 3,a &b respectively. After each one stage two dimensional wavelet decomposition, the two-dimensional input signal is projected onto four subspaces of low-low (LL), low-high (LH), high-low (HL), high- high (HH) band frequencies. Further decompositions are applied over the low-low (LL) sub-band as shown in Fig. 3, while Fig. 4 gives the inverse Wavelet Transform computations.



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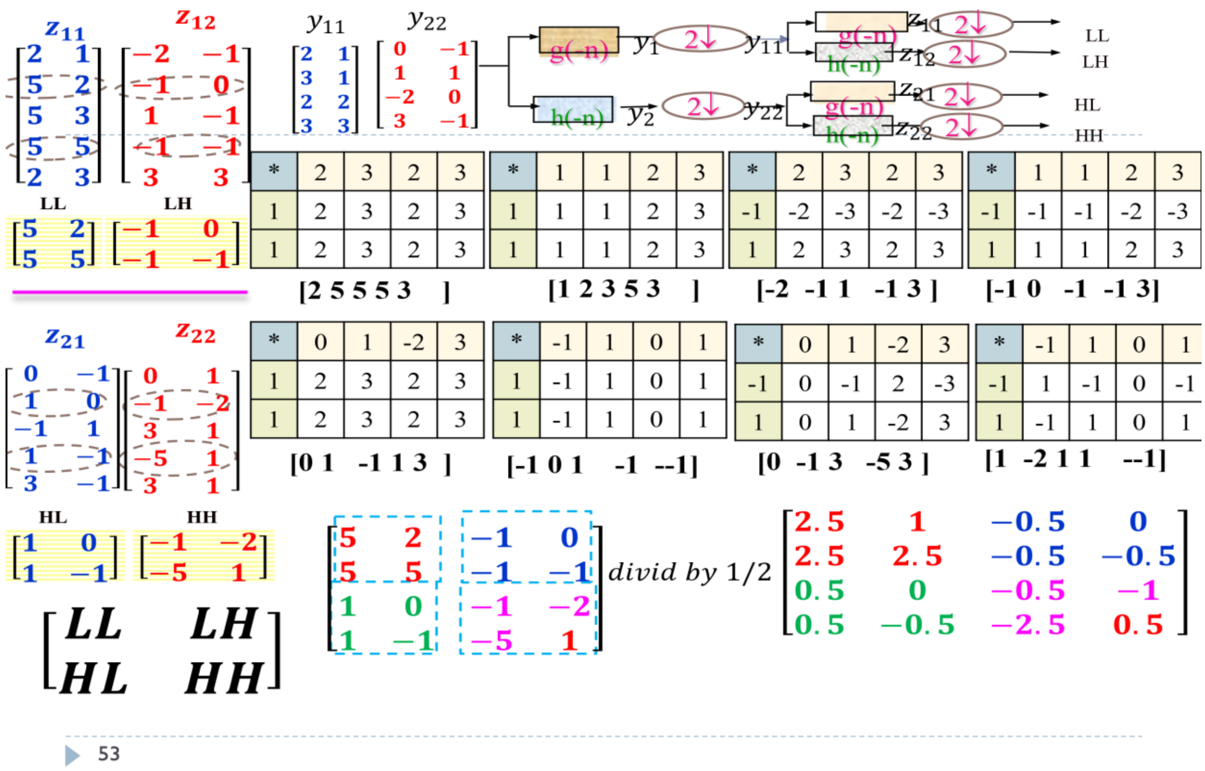

Fig. 3 *computation of two-dimension wavelet transform*

4. The Proposed Image Reconstruction Algorithm

The procedure of image reconstruction that dependent here is in two phases:

4.1. Generation of Reference Image Templates

The section deals with the problem of how to create reference templates from a large number of image sets via wavelet transform, feature extracting and recurrent neural network.

System data work with is a grayscale images of size 256 x256 each, with any type of image file format.

4.1.1. Procedure of Generating Images Templates:

1. Input an image to the generating algorithm.
2. Apply the wavelet transform up to 8-level of decomposition using doubciees discrete wavelet transform „db4" or any basic function-:

Decomposition the image using „db4" wavelet transform into 8-level, the levels are the low-low, low-high, high-low & high-high, Three images are of size 128 x128 which is the result from the 1-level of decomposition. Three of size 46 x 46 which is the result from the 2-level of decomposition. Three of size 32 x 32 which is the result from the 3- level of decomposition. Three of size 16 x 16 which is the result from the 4-level of decomposition. Three of size 8 x 8 which is the result from the 5-level of decomposition. Three of size 4 x 4 which is the result from the 6-level of decomposition. Three of size 2 x 2 which is the result from the 7-level of decomposition. Finally Three of size one element which is the result from the 8-level of decomposition.

The result will be 25 sub images from 8-decomposition. Shows the convention of each level of decomposition for displaying the „db4" daubchies wavelet transform of an image.

3. Calculation of energy feature of the wavelet coefficient for the result sub images-:

The energy feature will be computed for the 25-subimages, one value of energy is computed, the feature vector will have 25 energy values. This feature vector will be used in the reconstruction procedure. This means that each sub-image will have one energy value only .

The elements of the feature vector will be ordered like (energy value of sub-image 1, energy value sub-image 2, energy value sub-image 3, …, energy value of sub- image25).

4. Construction of a structure for the image-:

This structure contains image class label, image name and energy feature vector for each of the 25-subimages result from step 3. for example:

Image Struct= (class label, name, feature vector (of 25 elements)).

5. Repeat the steps- :

From 1-5 for all images concerned with the reconstruction system application.

4.2. The Reconstruction Phase:

The three aspects of the image reconstruction approach are:

1. The selection of features.
2. The choice of a measure of similarity.
3. A method for creating reference templates.

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4.2.1. The Proposed Reconstruction Procedure:

A block diagram for the proposed reconstruction procedure is given in figure (6).

1. Input the Image:

The given image to the reconstruction system is application.

2. Application of the discrete Wavelet Transform to the unknown Image:

In this stage the given image to the system will be decomposed using tow-dimension discrete wavelet transform using „db4" basic function. The image will be decomposed into 8-levels. The results of the decomposition will be 25 sub-images.

3. Feature Extraction:

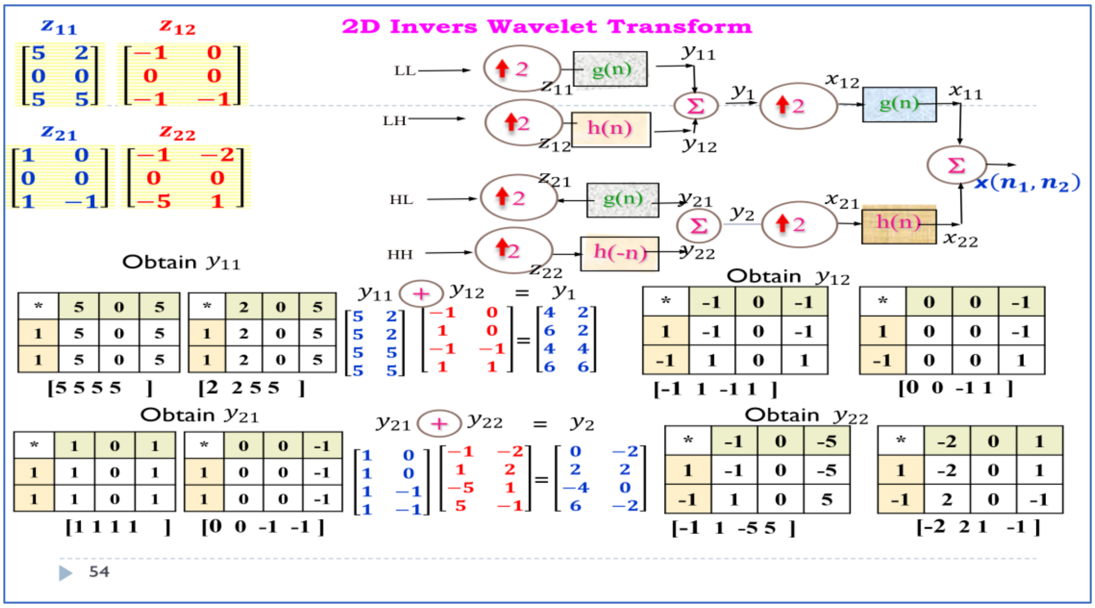
In this stage the energy feature (explained in the previous section) will be computed for the 25-subimage resulting from the previous stage. Hence the resultant feature vector of size 25 elements will be constructed.

4. Reconstruction:

Having defined as feature vector per image, the remaining problem is to reconstruction them, i.e. associate each vector with an index that corresponds to a particular class. One of the important steps in the image reconstruction task is that classification process. A feature vector is then assigned a class label according to its position in feature space. Testing the performance of the classifier require an independent test set of labeled samples. Then it will be reconstruction to the lost blocks image from the original image of the reference set. The reconstruction is used depends on the Elman Recurrent Neural Network (*ERNW*). The input to the network will be sequence of feature extraction input vector consist of 25 values will be trained & test, when Elman networks can be trained with either of two functions, train as the following occurs at each epoch:

1. The entire input sequence is presented to the network, and its outputs are calculated and compared with the target sequence to generate an error sequence.
2. **For** each time step, the error is back propagated to find gradients of errors for each weight and bias. This gradient is actually an approximation since the contributions of weights and biases to errors via the delayed recurrent connection are ignored.
3. This gradient is then used to update the weights with the backprop training function chosen by the user. The function training is recommended.

Then to unknown image, the reconstruction procedure will be the calculation some squire error among the set of the images in the reference set find the minimum result in the test phase in the ERNW on the feature vector of the image reference and matching it with unknown image and the smallest number of the results set will be the original image for the unknown image. So will go to the next stage to know the reconstruction image.



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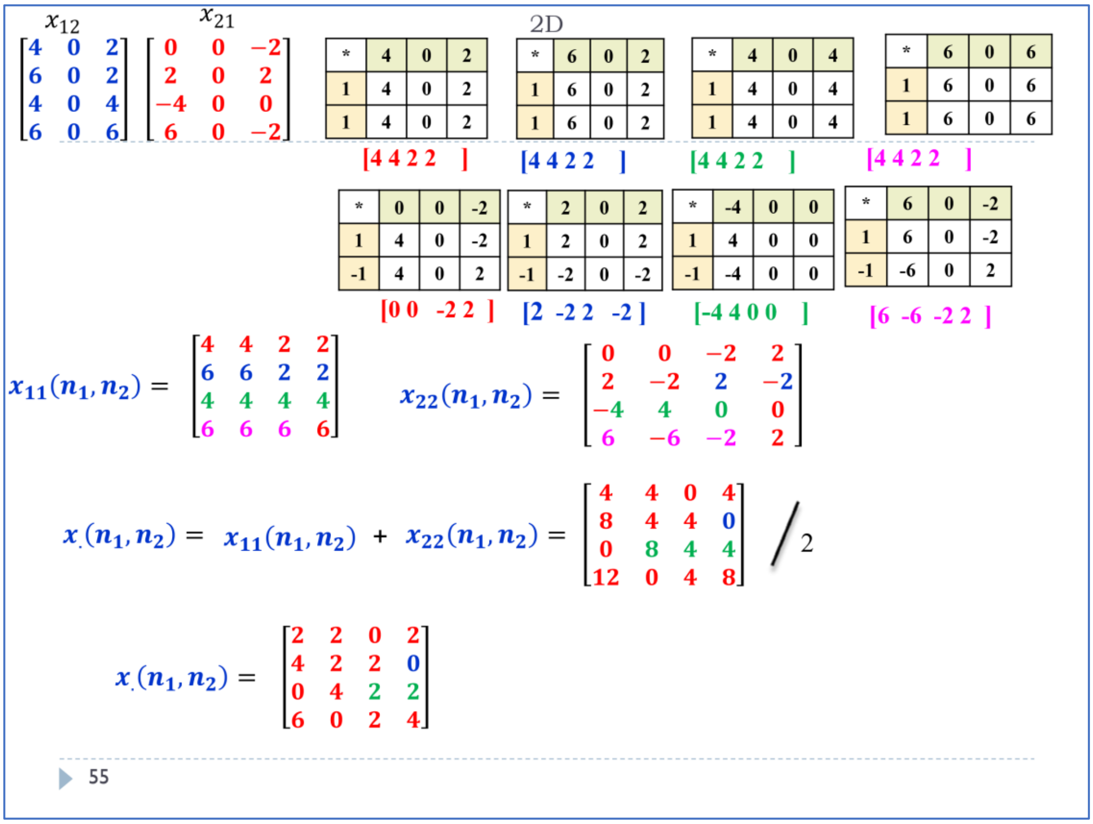

Fig. 4*: Inverse Wavelet transform computation*

5. LOGICAL DECISION:

In this procedure a comparison is to be performed on the reconstructed image with a reference set, in order to reach a logical decision and find the original image complete the uncompleted image with the original image to find the missing parts of the uncompleted image. Display the uncompleted image or missing parts of image and reconstructed the image, as shown in Fig. 5.

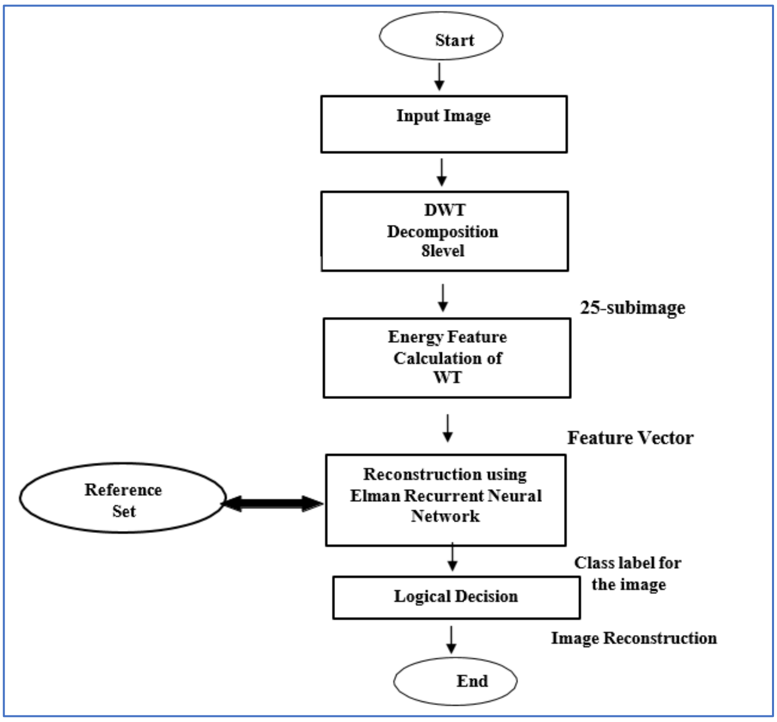

Figure 5: *Block diagram for the image reconstruction using Wavelet Transform & ERNW*

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Volume 8, issue 4. 2025

6. EXPERIMENTAL RESULT:

In this experiment m12a1is considered after lost small blocks in different area pixels.

1. The entered unknown image, figure 6-a
2. Daubechies "db4" DWT decomposition into 8-level, figure 6,b,c,d,e,f,g,h,i.
3. Feature extraction: the completed energy vector for 25-subimage is= (1.0e+007 * 0.0002 0.0003 0.0000 0.0002 0.0001 0.0000 0.0010 0.0010 0.0001 0.00150.0019 0.0011 0.0057 0.0067 0.0091 0.0393 0.0126 0.0262 0.0645 0.08920.0131 0.2262 0.2236 0.0283 1.8450)
4. Classification: calculate some square error between energy of the unknown image and all the feature vector of the images stored in the reference set. The unknown image classified as class label I12 the test result of some square error between image energy.
5. Reconstruction: this label class that comes from the pervious stage must be reconstructed, by using logical decision. In this experiment, the unknown image will be reconstructed we complete the lost block of missing unknown image, as Struct= (m12a1, c:\MATLAB6p1\toolbox\imdemo\m12a1, 1.0e+007 * (0.0002 0.0003

0.0000 0.0002 0.0001 0.0000 0.0010 0.0010 0.0001 0.0015 0.0019

0.0011 0.0057 0.0067 0.0091 0.0393 0.0126 0.0262 0.0645 0.0892

0.0131 0.2262 0.2236 0.0283 1.8450)) the reconstruction result was true.

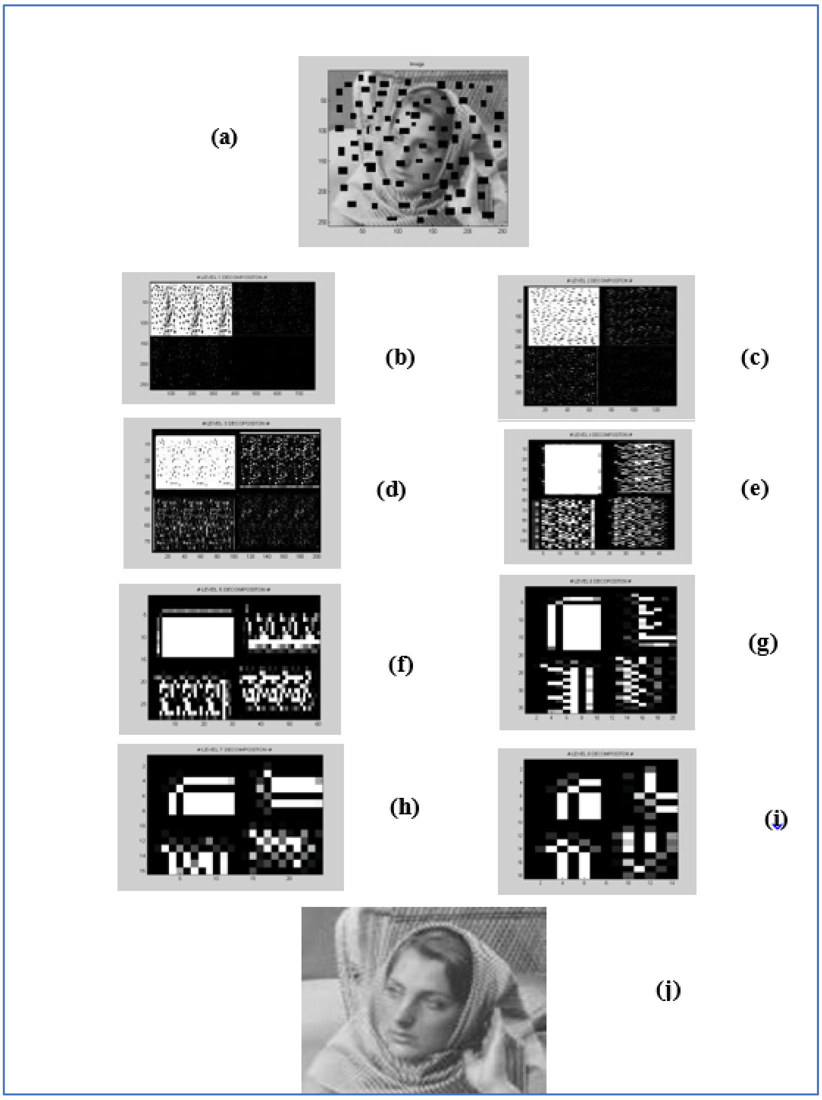

***Figure 6: a)** The lost block image, **b)** the first level of decomposition, **c)** the second level of decomposition, **d)** the third level of decomposition, **e)** the forth level of decomposition, **f)** the fifth level of decomposition, **g)** the sixth level of decomposition, **h)** the seventh level of decomposition, **i)** the eighth level of decomposition, **j)** the Image Reconstruction.*

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7. Analysis And Comparison Of The Proposed Method With Other Methods

Based on the results obtained, table 1 gives comparison of the three methods for image reconstruction, namely the Wavelet Transform, the Neural Network, and a hybrid of the two.0

Table -1: *comparison of image reconstruction using WT, NN, and a hybrid of the two*

Feature	Wavelet Transform (Alone)	Neural Network (Alone)	Hybrid (Wavelet + Neural Network)
Methodology	Decomposes images into different frequency components. The inverse transform is then used to reconstruct the image.	Learns a complex, non-linear mapping from degraded images to high-quality images using a large training dataset.	Uses a wavelet transform to decompose the image first, then applies a neural network (often a CNN) to process the resulting frequency components.
Strengths	- Multi-resolution analysis: Excellent at analyzing an image at different scales and frequencies. - Computational efficiency: Generally faster than neural network methods, especially for reconstruction tasks like denoising. - Signal sparsity: Natural signals are often sparse in the wavelet domain, which makes them highly compressible.	- Superior performance: Can achieve higher reconstruction quality (e.g., higher PSNR and SSIM) than traditional methods like wavelets. - Learns complex patterns: Excels at learning intricate, non-linear relationships and can handle a variety of degradation types. - Data-driven: Its performance improves with more training data.	- Combines the best of both: Leverages the multi-resolution analysis of wavelets for feature extraction and the powerful learning ability of neural networks for complex pattern recognition. - Improved performance: Often outperforms both standalone methods by reducing noise, suppressing artifacts, and preserving fine details more effectively. - Increased efficiency: The wavelet decomposition can simplify the task for the neural network, potentially leading to faster training and better results.
Weaknesses	- Limited adaptability: Less effective at handling complex or unknown degradations in an image, as it relies on a fixed mathematical transformation. - Artifacts: Can sometimes introduce blurring or artifacts, especially around edges, depending on the chosen wavelet.	- Requires large datasets: Performance is heavily dependent on having a vast amount of high-quality training data. - Computational cost: Training is computationally expensive and time-consuming. - Black box nature: It can be difficult to interpret why a neural network produces a specific output.	- Increased complexity: The system is more complex to design and implement than a single-method approach. - Tuning challenge: Requires careful tuning of both the wavelet parameters and the neural network architecture.
Typical Use Cases	- Image compression (e.g., JPEG2000). - Denoising. - Medical imaging (e.g., CT reconstruction).	- Super-resolution. - Medical image reconstruction (e.g., from fMRI data). - Denoising and inpainting.	- Sparse-view CT reconstruction. - Image denoising. - High-resolution image restoration. - Medical image analysis and classification.

8. CONCLUSIONS

As shown in Fig. 7, to reconstruct uncompleted image with missing blocks or parts, the image must be classified correctly to lead to good reconstruction. The wavelet energy by implementing the 2-DWT into 8-level and computing the energy for the result. The result is computed only once and saved in a file as training information. Wavelet transform Daubechies “db4” basic function has advantage that provide a good energy localization in the frequency domain as other wavelet transforms. This makes Elman networks useful in such areas as signal processing and prediction where time plays a dominant role.

Test these images using the proposed algorithm are done by using wavelet transform, feature extraction with Elman recurrent neural network (ERNW), and the result of testing was 100% accuracy. It gave good reconstruction uncompleted images automatically.

Thes results are obtained since the Neural networks produced a higher quality reconstructed image with fewer artifacts and less blurring compared to conventional methods. They are adept at learning complex, non-linear relationships within image data, which allows them to effectively remove noise and fill in missing information while preserving fine details and structures.

Once trained, a neural network can perform image reconstruction almost instantly. This is a significant improvement over many traditional iterative reconstruction algorithms that can be computationally intensive and time-consuming. This speed makes neural networks suitable for real-time applications, especially in fields like medical imaging where fast results are crucial.

As future work, the use of optimal algorithms improve further the performance of the system [47]-[60].

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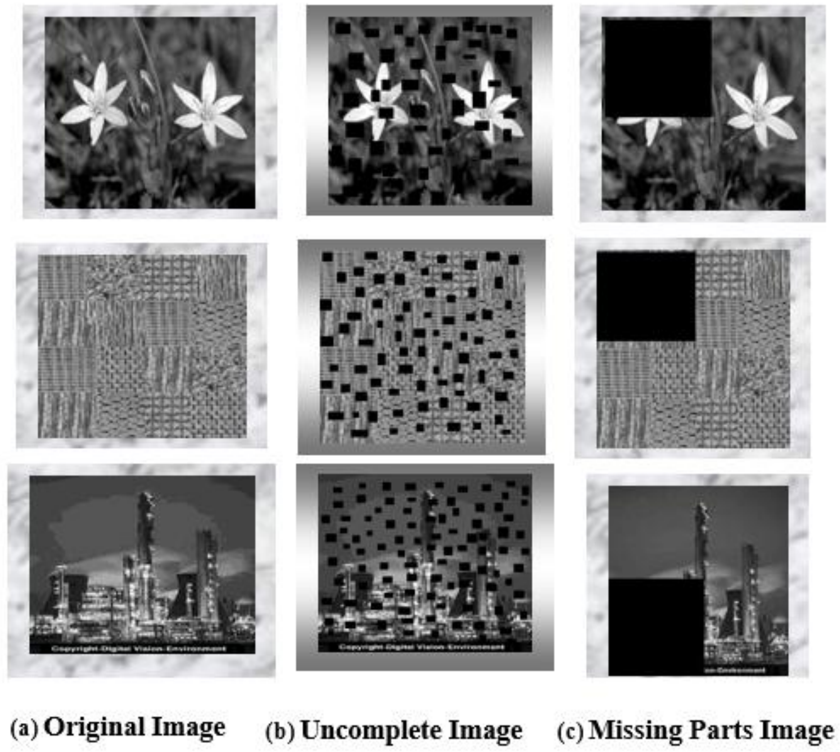

Figure 7**: samples of Generated Versions of some Images.* ***(a) *Original Image,* ***(b)*** *Uncomplete Image****,*** ***(c)*** *Missing Parts Image*

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