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Enhancing Medical Image Classification: A Deep Learning Perspective with Multi Wavelet Transform

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Abstract, Classification of medical images is a very important area of research for both the medical industry and academia. In recent years, automated classification algorithms have become very important in most medical applications, saving time and effort, such as disease detection and diagnostic radiology. Deep learning offers a plethora of advantages when applied to medical image classification, revolutionizing medical diagnosis and patient care. In this study, deep convolutional neural networks (DCNNs) is used to classify medical im-ages and multi-wavelet transform will be applied to extract features. The proposed method aims to improve medical image classification accuracy, thereby assisting healthcare professionals in making more accurate and efficient diagnoses. DCNNs based on the VGG16 model were trained and used in this study. Combining VGG16, a powerful convolutional neural network (CNN), with multiwavelet transform offers several advantages for image processing and analysis tasks, particularly in areas like image classification and feature extraction. To evaluate the performance of the proposed method six publicly available brain tumour MRI datasets are analysed with DCNNs. A fully connected layer is used to categorize the extracted features. According to the results, the deep CNN model combined with the multi-wavelet trans-form achieves an impressive accuracy of 96.43 %. It is evident from this high level of accuracy that the proposed approach is effective in accurately classifying medical images.

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Keywords: *Convolutional Neural network, multi-wavelet deep learning, medical image classification.*

1. INTRODUCTION

To improve the diagnosis of medical images, the most important features are extracted from the image. Extracting these features leads to the generation of a strong system that enables us to detect and diagnose the disease correctly and quickly. Extracting the most relevant characteristics from medical images is the focus of medical image analysis, which aims to enhance clinical diagnosis. The use of accurate positive and negative inferences from medical image classification models results in a reliable content-based image retrieval system [1]. Several researchers have used different algorithms for the purpose of diagnosing medical images and discovering diseases [2], [3][4], Ko et al.[5] Extracting the most relevant characteristics from medical images is the focus of medical image analysis, which aims to enhance clinical diagnosis. Using wavelet based symmetric binary patterns to improve classification performance for medical detection. Qasem et al. [6] Multi-objective optimization technique was used to generate centres and weights simultaneously for a radial basis function network. Krawczyk et al. [7] use technique to recover mammograms from a clinical setting. Breast thermograms may be analyzed using a technique devised that relies on images attributes. They suggested a neural network support vector machine (SVM) hybrid multiple classifier approach and developed a fuzzy metric to evaluate the ensemble's diversity. In addition, Tsochatzidis et al. [8] content-based image retrieval system has been integrated into a computer-aided diagnostic system to assist radiologists in the characterization of mammographic masses. Due to the vast array of hyper parameters and algorithmic options, designing a deep convolutional neural network for a given issue is anything but simple[1][9][10]. Another benefit of CNNs' lack of interpretability is that it allows them to be used with other well-studied signal processing methods [38]. By breaking down an image into its component frequencies, the discrete wavelet transform (DWT) [39] may aid in the feature extraction of a convolutional neural network (CNN)[1][11][12]. There is a good theoretical consideration of the wavelet characteristics in multiresolution signal processing in CNNs. For instance, Williams et al. [13] supplied CNNs a fresh input consisting of the wavelet sub-bands of the original image [40]. To top it all off, Oyallon et al. [14] suggested a wavelet scattering network as an alternative to ResNet's first hidden layer [[48]. The performance of this hybrid network is equivalent to that of ResNet, but with fewer hyper parameters. The challenge of organ tissue segmentation was also investigated by Lu et al. [15] who looked at a CNN enhanced with a dual-tree wavelet

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transform [49]. To further subsample features, Williams et al. [13] developed a wavelet pooling approach based on a second-level wavelet decomposition. Recommended using convolutional neural networks (CNNs), discrete wavelet transforms (DWTs), and long short-term memory (LSTM) together to identify liver and brain tumors [41]. Additionally, this study aims to investigate an effective pre-processing stage for obtaining meaningful information for CNNs [42]. However, this paper utilized Multiwavelet transforms and Deep Convolutional Neural Networks (VGG16) due to their ability to remove noise and outliers from images [[43]. Therefore, the main contribution of this study is a CNN-based classification model that is fed with approximate features derived from a multi-wavelet transform which have the following advantages:

1. Enhanced Feature Extraction.
2. Improved Noise Reduction and Denoising.
3. Increased Robustness and Generalizability.
4. Potential for Efficient Compression and Transmission.
5. Potential for Medical Image Analysis

Following is a summary of the rest of the paper. In Section 2, technical and fundamental aspects of the proposed model and other competing methods are described. The proposed medical image architecture is described in Section 3. Section 4 presents experimental results and discussion, followed by Section 5 which contains conclusions and future work.

2. MEDICAL IMAGE CLASSIFICATION SYSTEM

Medical image classification is a vital component of modern healthcare, facilitating accurate and timely diagnosis of various diseases and conditions [50]. With the increasing availability of digital medical imaging modalities such as X-rays, CT scans, MRI, and ultrasound, the volume of medical image data has grown exponentially. Manual interpretation of these vast datasets is time-consuming [44], error-prone, and often impractical, necessitating the development of automated and reliable medical image classification systems [45]. In recent years, artificial intelligence and deep learning have made significant advances in the field of medical image analysis [46]. It has been demonstrated that deep learning techniques are highly effective in computer vision tasks, such as image classification, particularly Convolutional Neural Networks (CNNs). Furthermore, these networks can learn and extract complex features from images, as well as distinguish patterns associated with different medical conditions[16]. Deep CNNs have shown promising results for diagnosing cancer, detecting neurological disorders, identifying diabetic retinopathy in retinal images, and detecting skin conditions in medical images [51]. It is possible to process and analyse large volumes of medical images with unprecedented accuracy, consistency, and efficiency[17]. Medical image preprocessing plays an important role in medical image classification systems. The input data is pre-processed using techniques such as image enhancement, normalization, and denoising to remove any artifacts or noise that may interfere with classification accuracy [52]. In addition, feature extraction involves converting raw image data into a more meaningful representation, enabling CNNs to learn relevant patterns more quickly [18]. For enhancing feature extraction, wavelet transforms are commonly used [53]. The Multiwavelet transform captures local and global characteristics of the image data at multiple resolutions [54]. A combination of deep CNNs and wavelet transforms has been shown to improve classification accuracy and robustness[19]. A deep CNN combines with multi-wavelet transforms in this article to classify medical images [55]. Healthcare professionals will be able to make timely and accurate diagnoses with the proposed system by addressing the challenges associated with accurate medical image classification [56]. Figure.1. illustrate the proposed system diagram. Deep learning models can extract complex and subtle features from medical images that might be missed by human eyes, leading to significantly higher accuracy and specificity in disease detection and classification. This translates to early detection of diseases, improving treatment outcomes, reduced chances of misdiagnosis, saving lives and resources and finally more personalized and targeted treatment plans based on accurate diagnoses. Deep learning models can automate manual image analysis tasks, reducing the workload on radiologists and other healthcare professionals. This allows for faster diagnosis and treatment decisions, saving valuable time and improving patient care efficiency. Additionally, automation reduces human error and subjectivity, ensuring consistent and reliable results. Deep learning models can learn from large datasets of diverse medical images, making them more generalizable to different patient populations and disease presentations. This reduces the need for retraining for specific applications, making them adaptable to evolving medical practices and new disease discoveries. Furthermore, deep learning models can be constantly improved by incorporating new data, ensuring their continued effectiveness over time. Deep learning relies on medical images, a non-invasive diagnostic tool, eliminating the need for potentially risky and expensive procedures like biopsies or exploratory surgeries. This provides a safer and more comfortable experience for patients while reducing healthcare costs associated with invasive procedures.

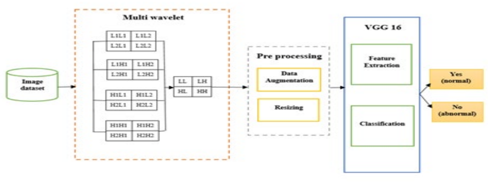

Figure. 1 *proposed MULTI-DNN System diagram*

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2.1 . Brief History of A Wavelet to Multiwavelet Transform

As a result of their ability to capture both time and frequency information effectively, wavelet transforms have gained substantial attention in signal and image processing[20]. Various applications have been improved by multiwavelet transforms, which have improved the properties and performance of wavelet transforms over time[21]. In contrast to scalar wavelets, multiwavelets exhibit orthogonality, symmetry, compact support, and vanishing moments [57]. By preserving energy during decomposition and preventing signal leakage, orthogonality minimizes redundancy. Symmetry ensures a linear or generalized linear phase of filter banks, effectively mitigating reconstruction errors and reducing distortion at the boundaries [22]. Due to the compact support property, boundary signal processing is highly accurate by avoiding truncation errors. An important attribute of multi-scaling functions is the approximation order, which quantifies precision. Higher approximation orders correspond to more refined approximations [23]. An important property of multiwavelet functions is the disappearing moments, which characterize the local Holder exponent. Signals with a higher vanishing moment can be accurately represented by scaling functions [24]. Geronimo–Hardin–Massopust (GHM) multiwavelets are among the earliest and most widely used multiwavelets with multiplicity 2 [25]. As an example, a GHM multiwavelet has orthogonality, symmetry, compact support, vanishing moment 2, and approximation order 2. Multiwavelets satisfy two-scale refinement equations:

$$\Phi(t)=\sum_{k=0}^{N} H_K \Phi(2t-K) \qquad (1)$$
$$\psi(t)=\sum_{k=0}^{N} G_k\, \Phi(2t-K) \qquad (2)$$

Where $H_K$and G_k are lowpass and highpass matrix filter banks respectively. K=0,1,…,N is the number of filter banks. By the dilations of the above equation the relationship between the coefficients

$(C_{1,j,k}, C_{2,j,k})^T$ And $(d_{1,j,k}, d_{2,j,k})^T$ can be obtaned.

$$\begin{pmatrix} c_{1,j,k} \\ c_{2,j,k} \end{pmatrix} = \sqrt{2}\sum_{n=0}^{K} H_n \begin{pmatrix} c_{1,j,2k+n} \\ c_{2,j,2k+n} \end{pmatrix}, j, k\epsilon Z \qquad (3)$$

$$H_0 = \begin{bmatrix} 3/5 & 4\sqrt{2}/5 \\ -1/10\sqrt{2} & -3/10 \end{bmatrix}, \quad H_1 = \begin{bmatrix} 3/5 & 0 \\ 9/10\sqrt{2} & 1 \end{bmatrix}$$
$$H_2 = \begin{bmatrix} 0 & 0 \\ 9/10\sqrt{2} & -3/10 \end{bmatrix}, \quad H_3 = \begin{bmatrix} 0 & 0 \\ -1/10\sqrt{2} & -3/10 \end{bmatrix}$$

$$\begin{pmatrix} d_{1,j,k} \\ d_{2,j,k} \end{pmatrix} = \sqrt{2}\sum_{n=0}^{K} G_n \begin{pmatrix} c_{1,j,2k+n} \\ c_{2,j,2k+n} \end{pmatrix}, j, k\epsilon Z \qquad (4)$$

$$G_0 = \frac{1}{10}\begin{bmatrix} -1/\sqrt{2} & -3 \\ 1 & 3\sqrt{2} \end{bmatrix}, G_1 = \frac{1}{10}\begin{bmatrix} 9/\sqrt{2} & -10 \\ 9 & 0 \end{bmatrix}$$
$$G_2 = \frac{1}{10}\begin{bmatrix} 9/\sqrt{2} & -3 \\ 9 & -3\sqrt{2} \end{bmatrix} \quad G_3 = \frac{1}{10}\begin{bmatrix} -1/\sqrt{2} & 0 \\ -1 & 0 \end{bmatrix}$$

Similarly, multiwavelet reconstruction can be obtained by:

$$\begin{pmatrix} c_{1,j,n} \\ c_{2,j,n} \end{pmatrix} = \sqrt{2}\sum_{n=0}^{K}\left(H_k^* \begin{pmatrix} c_{1,j,2k+n} \\ c_{2,j,2k+n} \end{pmatrix} + G_k^* \begin{pmatrix} d_{1,j,2k+n} \\ d_{2,j,2k+n} \end{pmatrix} \right) \qquad (5)$$

The results from simulation and experiments [26], [27] provide evidence that multiwavelet functions, which resemble fault features, can effectively extract fault characteristics from dynamic signals. However, conventional fixed and standard multiwavelet functions often do not adequately capture the unique features present in the signals. To overcome this limitation, it becomes crucial to construct customized multiwavelets with predefined properties, enabling accurate detection of fault features.

2.2. VGG16

Computer vision has been revolutionized by deep learning, which allows powerful models to be developed for the classification of images, the detection of objects, and the recognition of images[28]. There are a number of influential models in visual recognition, including VGG16, which is a deep convolutional neural network (CNN) architecture with remarkable performance. Researchers at the University of Oxford developed the VGG16 model, which has 16 weight layers[29]. During the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014, the VGG16 model achieved outstanding accuracy in classifying images into one of 1,000 predefined categories[30]. Its strong performance was attributed to its deep architecture and the use of relatively small 3x3 convolutional filters throughout the network. The key idea behind VGG16 is to stack multiple layers of convolutional, pooling, and fully connected layers to learn hierarchical features of increasing complexity. Figure 2 explain the vgg16 model layers. The network architecture consists of 13 convolutional layers, followed by three fully connected layers. In VGG16, smaller filters with a stride of 1 and padding allow the convolutional layers to capture intricate details and local features in images. Researchers have utilized the features extracted from VGG16's intermediate layers to detect objects, segment semantically, and transfer image styles. Due to the network's ability to learn rich hierarchical representations that capture different levels of visual information, it is versatile [31].

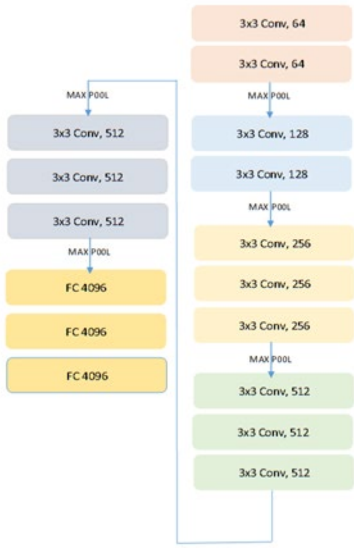

***Figure. 2** VGG16 model layers*

3. PROPOSED MEDICAL IMAGE ARCHITECTURE

Convolutional neural networks (CNNs) are combined with specialized modules and techniques for medical image processing in the proposed architecture. The design considers the unique characteristics and challenges associated with medical imaging, including high dimensionality, complex

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anatomical structures, and variability in image quality. Domain-specific preprocessing modules are a key component of the proposed architecture. Various challenges in medical image analysis are addressed by these modules, including noise reduction, image enhancement, and normalization. In order to enhance the performance of subsequent analysis steps, we apply these pre-processing techniques to enhance the quality and consistency of the input medical images. Furthermore, transfer learning is emphasized in the proposed architecture. By leveraging pre-trained models on large-scale medical imaging datasets or related tasks, we can benefit from learned representations and accelerate the training process. Transfer learning allows the model to generalize well to new medical image datasets with limited annotated samples, reducing the need for extensive labelled data. Extracting robust and discriminative features from images is crucial for accurate analysis and interpretation. VGG16's deep architecture with multiple convolutional layers excels at capturing spatial and semantic features, allowing for precise identification of objects and patterns. Multiwavelet Transform tool decomposes an image into different frequency bands, revealing hidden details and textures that might be missed by traditional methods. By combining VGG16's feature extraction capabilities with Multiwavelet transform's multi-resolution analysis, you can achieve a more comprehensive and nuanced understanding of the image content. Real-world images often contain noise: This can significantly impact the accuracy of image analysis tasks. VGG16, while powerful, can be susceptible to noise interference. Multiwavelet transform's ability to isolate and separate noise components from the actual image data comes in handy here. By applying Multiwavelet denoising techniques before feeding the pre-processed image to VGG16, you can significantly reduce noise artifacts and improve the overall quality of feature extraction. VGG16, trained on a massive ImageNet dataset, possesses a wealth of generalizable knowledge about various object categories and image patterns. However, its performance can be affected by specific image characteristics like illumination, viewpoint, and occlusions. Multiwavelet transform's ability to decompose images into different scales and orientations makes it robust to such variations. Combining it with VGG16 can lead to a more robust and generalizable model that performs well on diverse image datasets and real-world scenarios. Multiwavelet transform offers efficient image compression capabilities by discarding less important information in the higher frequency bands. This can be particularly beneficial for resource-constrained applications like image transmission over bandwidth-limited channels. Combining VGG16's feature extraction with Multiwavelet-based compression can lead to a system that extracts essential image features while significantly reducing the data size for efficient transmission and storage.

4. EXPERIMENT RUSTLES

4.1. Database

As part of the study, MRI scans of brain tumours were obtained from six different Kaggle databases as showed in table 1 in order to obtain the data used for this study. Several databases provide annotated images that can be used for analysis in these databases. Table 1 illustrate the databases that use in paper .mixed dataset, compiled MRI scans of brain tumours from six different Kaggle databases; each of these databases included a collection of annotated images.

Table 1: *tumour images dataset*

Dataset	Classes	Total number
First dataset [32]	[2,(without tumors , with malignancies)]	253 MRI
Second dataset [33]	[4,(glioma , meningioma, no tumor, pituitary tumor)]	3,264 MRI
Third dataset [34]	[3,(with tumor , without tumors, without labels)]	3,060 MRI
Fourth dataset [35]	[4,(without tumor, meningioma, glioma, pituitary tumors)]	7,023 MRI
Fifth dataset [36]	[2,(normal, tumor)]	400 MRI
Sixth dataset [37]	[2,(normal, signs of stroke)]	2,501 MRI
Mixed dataset	[2,(normal, abnormal)]	16,441 MRI

4.2. Evaluation Metrics Rustle

The evaluation metrics provide valuable insights into the performance of different classifiers for the Rustles dataset. Tables 2 and 3 show the evaluation results of the proposed system, which uses both the multi-wavelet algorithm and machine learning techniques. In particular, five different machine learning algorithms were used, including deep neural network (VGG16), decision tree (DT), support vector machine (SVM), naive Bayes (NB), and KNN (k-nearest neighbors). After careful analysis, it was found that the DNN

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algorithm provided the most favorable results when used with the proposed system. The proposed approach performs significantly better when machine learning algorithms are combined with the multiwavelet algorithm. Several algorithms were evaluated for their effectiveness in improving system performance, including Decision Tree, SVM, NB, and KNN. This particular system is best suited for machine learning algorithms based on the SVM algorithm, which provided the best results. Incorporating machine learning techniques in the proposed approach is a significant field advancement. These algorithms allow the system to learn and adapt to new data, making more accurate and efficient predictions. Based on the provided evaluation metrics, the Rustles classifier demonstrated favorable performance in terms of accuracy, sensitivity, specificity, precision, recall, G-Mean, and F1 Measure values. Further analysis and comparison of these metrics would provide a more complete understanding of the classifiers' performance on the Rustles dataset.

***Table 2**: tumour images dataset accuracy*

Dataset	DNN(Vgg16)	Multi-DNN
First dataset	0.8911	0.9505
Second dataset [33]	84.66	0.8850
Third dataset [34]	0.9444	0.9608
Fourth dataset [35]	0.8811	0.9238
Fifth dataset [36]	0.8250	0.9750
Sixth dataset [37]	0.8780	0.9240
Mixed dataset	0.9431	0.9640

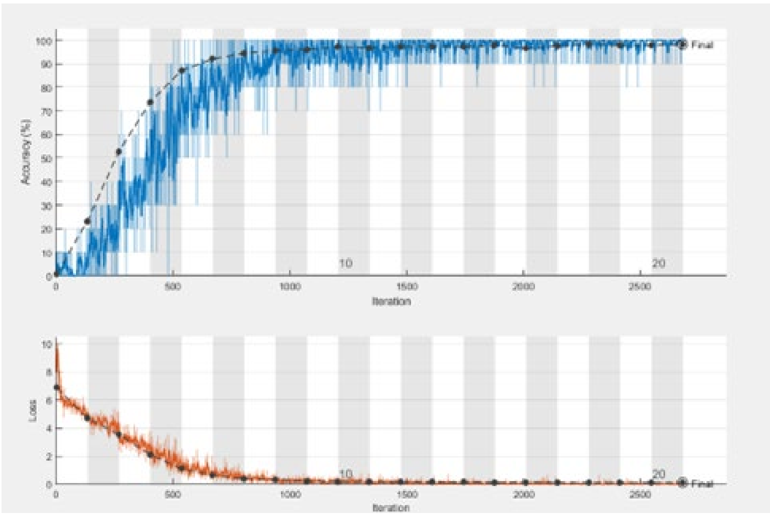

***Figure. 4** Accuracy and loss rate for mixed dataset*

The accuracy and loss of training of the proposed model shows on Figure. 4. Which represents Learning Rate over time. Typically, the learning rate decreases gradually during training. The loss should ideally decrease as training progresses. Analyze the loss curve to identify the convergence behavior. A smooth, decreasing curve indicates that the model is learning effectively, while erratic or plateauing behavior1 might suggest issues that require attention. Evaluate the final loss value achieved by the model. Lower loss values generally indicate better model performance.

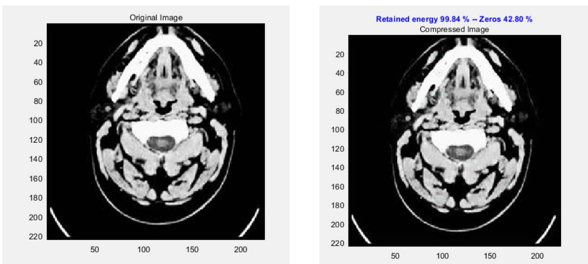

***Figure. 5** original tumour and compressed image*

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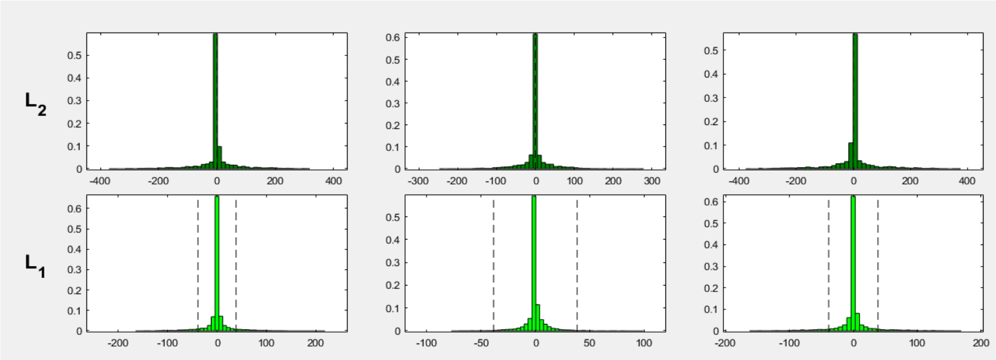

Figure. 6 *Histogram of multi wavelet coefficient of De-noise image*

Table 3: *evolution of proposed system*

Classifier	DNN	SVM	KNN	NB	DT
Accuracy	0.964	0.915	0.955	0.886	0.368
Sensitivity	0.948	0.942	0.956	0.922	0.936
Specificity	0.964	0.917	0.955	0.885	0.365
Precision	0.932	0.941	0.915	0.958	0.942
Recall	0.948	0.942	0.956	0.922	0.936
G-Mean	0.981	0.677	0.977	0.941	0.604
*F*1-Measure	0.911	0.917	0.895	0.925	0.915

Figures 5 and 6 show the image enhancement when applying a multi-wave transform, where the important details in the image are highlighted and compressed in order to be trained by deep neural network (VGG16 model).

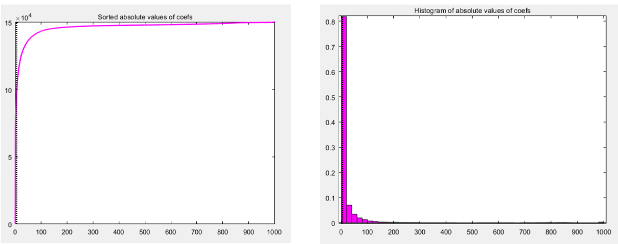

Figure. 7 *sorted absolute value and histogram of multiwavelet coefficient*

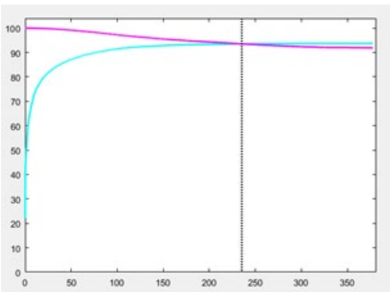

Figure. 8 *Retained energy and number of zero rate of pre-process image*

This study explored the effectiveness of multi-wavelet denoising and compression techniques for image enhancement. The aim to reduce noise while preserving essential image details and achieve efficient image compression. Figure 7 and Figure 8 illustrate the rate of image enhancement. By implementing multi-wavelet de-noising, we successfully reduced various types of noise from the images, such as Gaussian noise, salt-and-pepper noise, and random noise. The de-noising process effectively improved the image quality by reducing the visual artefacts caused by noise, resulting in enhanced clarity and sharper edges. Furthermore, by applying multi-wavelet compression techniques, we were able to achieve efficient image compression without significant loss of visual information. The compression process reduced the file size while preserving the essential details, leading to improved storage and transmission efficiency.

Overall, deep learning holds immense potential in medical image classification, transforming healthcare by empowering accurate diagnoses, efficient workflows, and personalized patient care. However, it's important to remember that deep learning technology is still under development, and challenges like data bias, interpretability, and ethical considerations need to be addressed for its safe and responsible implementation in medical practice.

5. CONCLUSION

For the classification of medical images, a deep CNN architecture in conjunction with a multi-wavelet transform is demonstrated. It has been concluded that deep learning and advanced signal-processing techniques can be combined to achieve high levels of accuracy in medical image analysis. By offering a tool that is efficient and accurate for the classification of medical images with a wide range of potential applications in the healthcare industry, the proposed approach

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contributes to computer-aided diagnosis. Future research can refine the architecture, explore different wavelet transforms, and extend the approach to other medical imaging modalities. As a result, the model's application and generalizability will be enhanced. The combined approach of VGG16 and Multiwavelet transform shows promise in medical image analysis tasks like disease detection and tumor segmentation. Multiwavelet transform's ability to highlight subtle details and textures can be valuable for identifying early-stage abnormalities, while VGG16's feature extraction capabilities can aid in precise tumor delineation.

Overall, using VGG16 with Multiwavelet or mixed [46] or hybrid [57] and others [49] offers a powerful and versatile combination for various image processing and analysis tasks. By leveraging the strengths of both approaches, you can achieve enhanced feature extraction [56], improved noise reduction [00], increased robustness [48], efficient compression [56], and potentially unlock new possibilities in medical image analysis.[50]

It's important to note that the specific benefits and challenges of this combination will depend on the specific application [58] and dataset [44]. Careful experimentation [51] and parameter tuning [55] are crucial for optimal performance [46]. Addition of optimizing metaheuristic algorithms [59] will further improve the performance of VGG16 [60].

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