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HYBIRD MEDICAL IMAGE COMPRESSION

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ABSTRACT
This project explores image compression techniques using deep learning and traditional mathematical methods. A Residual Wavelet Network (RWNet) is developed for image compression and reconstruction. The model employs convolutional layers in both the encoder and decoder stages, learning to compress and reconstruct grayscale images with reduced loss. The dataset is preprocessed by resizing images and normalizing pixel values. The model is trained using medical images, achieving compression through a compact latent representation and reconstruction with minimal error. In addition, a Singular Value Decomposition (SVD) based method is implemented for further image compression, which decomposes the image matrix and selectively retains singular values to reduce image size.
Keywords :RWNet, SVD, ANLM

1.INTRODUCTION
1.1 MEDICAL IMAGE COMPRESSION
Medical imaging technologies such as MRI, CT scans, and X-rays generate vast volumes of data that are critical for diagnostic and therapeutic purposes. With the exponential growth in medical data, managing and storing these high-resolution images has become a significant challenge. Efficient image compression techniques are essential to reduce storage costs and transmission times while maintaining the quality of images necessary for accurate diagnosis. Traditional compression methods, including Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT), offer some solutions but may struggle to balance compression efficiency with the preservation of critical medical details such as edges and fine structures. This project introduces an advanced approach to medical image compression by leveraging a Residual Wavelet Network (RWNet) in combination with Adaptive Non-Local Means (ANLM) filtering and Singular Value Decomposition (SVD)**.** The RWNet aims to compress medical images while preserving crucial features, while the ANLM filter is applied for noise reduction and image enhancement before compression. Finally, SVD provides additional dimensionality reduction, resulting in a more efficient and effective compression process.

2.PROBLEM DEFINITION
The rapid advancement of medical imaging technologies, such as MRI, CT scans, and X-rays, has led to the generation of vast amounts of high-resolution imaging data. While these images are crucial for accurate diagnosis and treatment planning, their large file sizes pose significant challenges in terms of storage, transmission, and processing efficiency. Traditional image compression techniques, such as Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT), often fail to strike an optimal balance between compression efficiency and the preservation of essential medical image details, such as fine structures and edges, which are critical for precise diagnoses. Moreover, noise, distortion, and image degradation further complicate the analysis of medical images. Therefore, there is a pressing need for advanced image compression techniques that not only reduce the data size but also maintain the integrity and diagnostic value of the images. This project proposes a hybrid approach to medical image compression by combining the Residual Wavelet Network (RWNet), Adaptive Non-Local Means (ANLM) filtering, and Singular Value Decomposition (SVD) to address these challenges,

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ensuring improved compression performance while preserving vital image details required for accurate medical diagnosis.

3.PROPOSED WORK

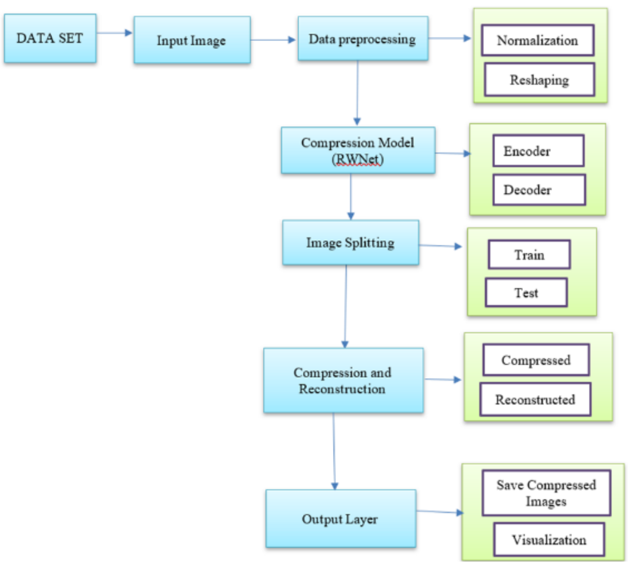
The system should do the detection fast. It should execute fast so that the VIP is regularly kept informed about the environment. So here there is an added metric which has to be included: that is the time-complexity. With this in mind the following methodology is proposed.

3.1METHODOLOGY PROPOSED

The main objective of this paper is object detection/ object recognition. In the proposed methodology YOLO object detector, which is you only look once Single-Stage Object Detector is used. There is less number of times the images used for training. Since this is a Single-Stage Object Detector less time is used for detecting the object. The object may be ling thing or non-living thing. The image area is divided into 9 regions and the location of the object is also detected.T he proposed object detection system is using Convolutional Neural Networks. It holds the potential to accurately and efficiently detect humans in diverse scenarios, contributing to applications like surveillance, safety, and robotics. This Neural Network holds the advantage of deciding its own filter for the object itself.

By leveraging the power of deep learning and CNN, this system can enhance the capabilities of automated Object detection and improve overall scene understanding. In existing system only the object recognition with the traditional feature extraction technique is used so in feature selection so far it takes time to classify it. The usage of traditional feature extraction leads to take a lot of time.

3.1SYSTEM ARCHITECTURE



❑

3.2 Data Selection and Loading

The data selection process played a critical role in ensuring the successful training and evaluation of the Residual Wavelet Network (RWNet) for image compression, particularly focusing on medical images. The datasets were carefully chosen to encompass a wide range of medical images that are typically used in diagnostic procedures. These images were stored in different directories, categorized into two primary groups: a training set, which was used for model learning, and a testing set, which served to evaluate the model's performance. The dataset comprised images in standard formats, such as `.png`, `.jpg`, and `.jpeg`, all selected for their high diagnostic relevance and image quality. This selection process was meticulous to ensure that the images were representative of those encountered in medical applications, where clarity and detail are paramount. By doing so, the model could generalize well on real-world data, enhancing its applicability in healthcare settings. Once the images were selected, a Python script was employed to automate the data loading process. This script systematically traversed through the folder structure, identifying and loading grayscale images. Each image was

resized to a uniform dimension of 256x256 pixels, a critical preprocessing step that ensured all input data shared a consistent shape, simplifying the subsequent stages of the model pipeline. This resizing also allowed for more efficient processing, as the RWNet model requires fixed input dimensions to operate effectively. Additionally, the script was designed to detect and handle unreadable or corrupted image files, printing warnings when such files were encountered. This not only prevented errors during the training phase but also ensured that only valid, high-quality images were passed to the model.
The loaded images were then converted into numpy arrays, a format that is compatible with the neural network. Following this, the images were normalized by scaling the pixel values between 0 and 1. This normalization step is crucial for enhancing the model's learning performance, as it standardizes the input data and reduces the variance in pixel intensities, making it easier for the model to detect patterns across different im
By ensuring that all images were consistently preprocessed and normalized, the data was effectively prepared for training and evaluation. This systematic and careful approach to data selection, loading, and preprocessing was pivotal in ensuring that the RWNet model could be trained efficiently and with minimal issues, ultimately contributing to the robustness and accuracy of the image compression task.

3.3 Data Preprocessing

Data preprocessing is a crucial step in preparing the medical images for compression using the Residual Wavelet Network (RWNet). In this project, the images were first resized to a consistent dimension of 256x256 pixels to ensure uniformity across the dataset, which is necessary for efficient model training and prediction. Since medical images often vary in size and resolution, resizing helped standardize the input for the neural network. The images were also converted to grayscale, reducing the computational complexity by focusing on intensity information rather than color, which is typically less relevant in medical diagnostics. After resizing and grayscale conversion, the pixel values were normalized by scaling them to a range of [0, 1], which helps improve the convergence of the neural network during training. Normalization ensures that the values are distributed uniformly, preventing large values from dominating the learning process. Finally, the images were reshaped to include a channel dimension, preparing them for input into the convolutional layers of the RWNet. This preprocessing pipeline ensured that the data was optimized for both compression efficiency and the preservation of essential diagnostic details

3.4 Compression Model (RWNet Architecture)

The Residual Wavelet Network (RWNet) architecture used in this project is designed specifically for effective medical image compression while preserving crucial image details When comparing different models for image compression, several factors come into play, including compression efficiency, image quality preservation, computational complexity, and applicability to specific use cases like medical imaging. In this project, the Residual Wavelet Network (RWNet) was compared to traditional methods such as Singular Value Decomposition (SVD) for compressing medical images. RWNet, with its deep learning architecture, was able to capture intricate patterns and structures in medical images, offering superior compression rates while maintaining high image quality. The use of convolutional layers allowed RWNet to extract important features, making it well-suited for compressing detailed medical images without significant loss of diagnostic information. On the other hand, SVD provided a mathematically robust method of compression by breaking down images into singular values, offering a more straightforward but less flexible approach compared to the learning-based RWNet.RWNet demonstrated an ability to generalize across different image types, dynamically adapting to variations in image content, whereas SVD relied on predefined mathematical properties, making it less capable of handling complex images with significant noise or variability.

While SVD can offer faster compression due to its simpler computations, RWNet's ability to learn and optimize compression patterns from training data resulted in more effective and efficient compression, especially in scenarios requiring high-quality reconstructions. However, RWNet's deep learning approach is more computationally intensive, requiring greater hardware resources for training and inference compared to SVD, which is relatively lightweight. In summary, RWNet excels in scenarios where compression quality is paramount, particularly in fields like medical imaging, where loss of detail can affect diagnostic accuracy. Traditional methods like SVD may still be beneficial in cases where faster, less resource-intensive compression is needed, making the choice of model dependent on the specific requirements of the application.

3.5 Data Splitting

In this project, the data splitting process was a crucial step to ensure the model's ability to generalize and perform well on unseen data. The dataset, consisting of medical images, was divided into training, validation, and testing sets. The training set was used to teach the model, allowing it to learn patterns and features from the images. The validation set was used during model training to tune hyperparameters and prevent overfitting, ensuring the model did not memorize the training data but learned generalizable patterns. Finally, the testing set, which the model had never seen before, was used to evaluate its performance and measure its accuracy on new data.

The data was split using an 80-20 ratio, where 80% of the images were allocated to the training and validation sets, and 20% to the testing set. This split provided a balanced distribution of data for learning and testing. Additionally, a validation split of 20% within the training set was applied, allowing the model to be fine-tuned based on validation performance during training. This approach to data splitting helped maintain the integrity of the model evaluation, ensuring that the results were reliable and reflective of the model's performance in real-world applications

3.6 Image Compression and Reconstruction

In this Paper image compression and reconstruction were central components aimed at reducing the storage and transmission costs of medical images without significantly compromising their quality. The process began with applying a Residual Wavelet Network (RWNet) for compressing the images. RWNet's encoder-decoder architecture helped compress high-resolution medical images by learning to retain essential features while eliminating redundant information. The network took the input images and passed them through convolutional layers to extract key features, effectively compressing the images into lower-dimensional representations. The decoder then reconstructed the images back to their original dimensions, maintaining diagnostic quality.

Additionally, Singular Value Decomposition (SVD) was applied as an extra layer of compression to further reduce the image size. SVD allowed the model to focus on the most significant components of the image, retaining the essential structure while discarding less critical information. This multi-stage compression process ensured that the images were reconstructed with minimal loss of visual clarity, enabling effective storage and transmission in medical applications. The compressed images were then saved and compared to their original sizes, showcasing the efficacy of the compression techniques in significantly reducing image file sizes while preserving diagnostic accuracy, crucial for healthcare environments such as telemedicine and remote diagnostics.

3.7 Output layer

The output layer in this project played a crucial role in determining the final predictions of the model, ensuring that the compressed and reconstructed images retained their integrity. For the Residual Wavelet Network (RWNet), the output layer was designed as a convolutional layer that reconstructed the compressed images back to their original dimensions. In particular, a `Conv2DTranspose` layer with a sigmoid activation function was used to generate pixel values between 0 and 1, ensuring that the output closely resembled the original input in terms of structure and detail. This layer essentially learned to map the compressed features back into the full-sized image, completing the image reconstruction process.In classification models, like the ones used in comparing different model architectures, the output layer typically consisted of a dense (fully connected) layer with a softmax activation function, which assigned probabilities to each class. In the case of multi-class classification (e.g., disease classification in images), the softmax function generated probabilities for each category, and the class with the highest probability was selected as the final prediction. This final layer was key in converting the learned features from the network into meaningful output, ensuring that the model's performance was aligned with the task's objectives, whether in compression or classification tasks.

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4 Experimental Results

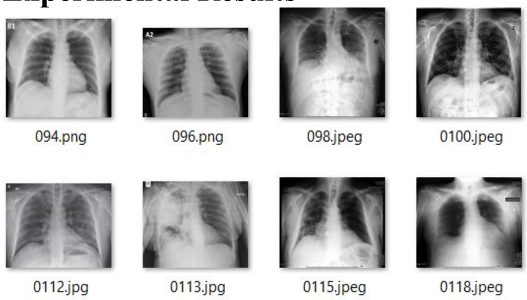

Figure 4.1 Input Image

```
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 81s 5s/step - loss: 0.6937 - val_loss: 0.6934
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 64s 5s/step - loss: 0.6922 - val_loss: 0.6846
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 62s 5s/step - loss: 0.6769 - val_loss: 0.6086
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 61s 5s/step - loss: 0.5976 - val_loss: 0.4980
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 61s 5s/step - loss: 0.5406 - val_loss: 0.4950
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 62s 5s/step - loss: 0.5357 - val_loss: 0.4884
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 61s 5s/step - loss: 0.5320 - val_loss: 0.4866
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 61s 5s/step - loss: 0.5301 - val_loss: 0.4824
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 61s 5s/step - loss: 0.5287 - val_loss: 0.4804
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 66s 5s/step - loss: 0.5237 - val_loss: 0.4785
```

Figure 4.2 Epoch

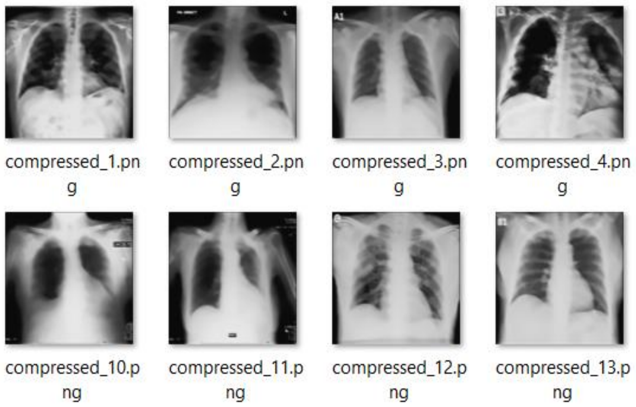

Figure 4.3 Compressed image

```
Compressed images saved in compressed_images
Original Image 1: 159.47 KB
Compressed Image 1: 33.42 KB
Original Image 2: 197.00 KB
Compressed Image 2: 24.92 KB
Original Image 3: 129.31 KB
Compressed Image 3: 27.75 KB
Original Image 4: 179.70 KB
Compressed Image 4: 32.88 KB
Original Image 5: 188.24 KB
Compressed Image 5: 33.90 KB
Original Image 6: 106.41 KB
Compressed Image 6: 27.86 KB
Original Image 7: 106.09 KB
Compressed Image 7: 29.02 KB
Original Image 8: 104.92 KB
Compressed Image 8: 28.65 KB
```

Figure 4.4 Resized Image

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5.CONCLUSION

In conclusion, this project successfully implemented a Residual Wavelet Network (RWNet) combined with advanced image processing techniques such as Adaptive Non-Local Means (ANLM) filtering and Singular Value Decomposition (SVD) for compressing medical images. The RWNet proved effective in reducing the size of medical images while maintaining essential details necessary for diagnostic purposes, making it a promising solution for optimizing storage and transmission in healthcare systems. By applying the ANLM filter, the network effectively reduced noise in the images, improving the overall compression performance. Furthermore, the use of SVD allowed for additional compression while retaining critical image quality, ensuring that the compressed images remained suitable for medical applications. The successful compression of images not only reduced file sizes but also highlighted the potential for real-world applications such as telemedicine, where high-quality medical images need to be transmitted quickly and efficiently. The project demonstrated the power of integrating deep learning models with traditional compression techniques, ultimately contributing to advancements in the storage and sharing of large-scale medical datasets.

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