

IMAGE FUSION FOR MEDICAL IMAGES USING DWT AND IDWT

Submitted in partial fulfillment of the
requirements for the award of
Bachelor of Engineering degree in Information Technology

By

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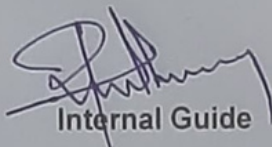
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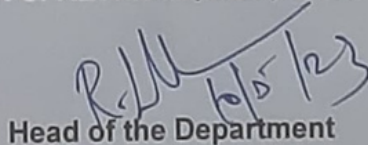
BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **ADHITHYA.V** who carried out the Project entitled "**IMAGE FUSION FOR MEDICAL IMAGES USING DWT AND IDWT**" under my supervision from March 2023 to May 2023.



Internal Guide

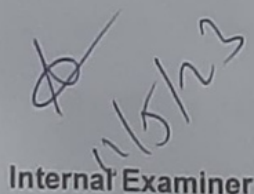
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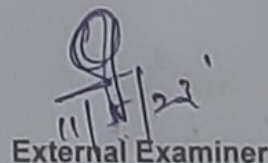
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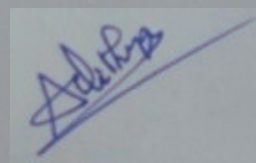
DECLARATION

I, **ADHITHYA.V (39120004)** hereby declare that the Project Report entitled "IMAGE FUSION FOR MEDICAL IMAGES USING DWT AND IDWT" done by me under the guidance of **Dr. S. REVATHY, M.E., Ph.D.** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Information Technology**.

DATE: 11-5-23

PLACE: Chennai

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ABSTRACT

Fusing different medical images will increase the accuracy in diagnosis of disease and describe the complicated relationship between them for medical research. In this model, we will retrieve the complicated information from different medical images like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) by fusing them through multi-stage fusion networks. Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces. Also in the existing model, CNN algorithm is used and it is not efficient. In the existing system, the fusion was not done properly and also the accuracy is very low. In the proposed model, we will use Dual Tree Complex Wavelet Transform (DTCWT) to extract the complicated and correlated information from each image and segmentation is done on fused image to get the segmented image. In the proposed method, the fusion of multi model medical images can be done by Dual Tree Complex Wavelet Transform, where the source medical image is converted to grayscale and decomposed, then the wavelet coefficients are extracted using DTCWT. After that, the approximation of wavelets are done to obtain the fused coefficients. Finally Inverse Dual Tree Complex Wavelet Transform is applied to obtain the final fused image. Additionally segmentation is performed to obtain the segmented image for the purpose of getting enhanced visual representation. In the proposed method, the improved quality of final fused image can be obtained.

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CHAPTER 1

INTRODUCTION

X-ray, Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) medical images, will not provide as much as detailed information for medical based research and diagnosis. They are required to provide a lot of elaborated clinical data. Medical imaging systems will provide different medical information regarding tissue, that are complicated in most cases. For example, X-rays, are used for identify bone injuries and bone fractures, CT images will give the elaborated information of internal organs, tumors and blood vessels. MRI is used to provide the information about tissues. Whereas the SPECT will show how blood flows to tissues and organs, and finally PET is helps to reveal how the tissues and organs are functioning.

All these features will not be gathered from a single image, in order to extract all the complicated information from a single we are fusing the medical images of single or different systems. The medical image fusion is defined as the process of merging different kinds of medical images or of similar types into a single image that provides more accurate information for diagnosis that will be helpful for better and accurate treatment. The doctors will able to extract the detailed and complicated data from the fused images of the medical images which are not visible in individual images.

Medical image fusion tools are used in the medical department like oncology and cancer research therapy. A perfect image fusion process should get the complementary information of the source images in final fused image while neglecting the unwanted and unexpected features. Before getting into the image fusion process, the source image should be preprocessed, that is the source image should be properly registered and aligned.

Image fusion can be done at three levels, they are pixel level, characteristics level and decision level. Pixel level fusion is designed to merge multiple source images into a final combined image, which will give more information for machine and human perception as compared to any of the source image. Next is the characteristics level

image fusion is also referred as middle level image fusion. This process can represent and analyze the multi-sensor data for realizing classification. This technique plays a vital role in theoretical and analytical tool for image and signal processing. The final level of image fusion is decision level, this is the process of combining information at a higher level and also merge the results from various algorithm to get a final fused decision. Here the input images are processed individually for information extraction.

The most common technique for image fusion is Discrete Wavelet Transform (DWT). In this fusion the resultant image will have the information like spectral and directional moreover, the directional information will include more accurate information on horizontal, vertical and diagonal directions. The discrete wavelet transform has two shortcomings, one is shift variance and the other one is directionality. The shift variance will lead to errors in fused images due to some small movement presented in the source image, and also due to poor directionality, the source image will become difficult for processing the geometric features like contours and edges.

To overcome this, the proposed method will fuse the different medical images based on Dual Tree Complex Wavelet Transform (DTCWT). The dual tree complex wavelet transform will be the solution for the shortcomings of Discrete Wavelet Transform (DWT). The DTCWT will provide better directionality and the shift variance which is easy to process the edges and contours of the source image. Increased shift variance and increased directionality features of the DTCWT make fulfilled image fusion tool.

SCOPE OF THE PROJECT

The fusion of multi-modality images plays an important role in medical imaging field as the extension of clinical use of various medical imaging systems. Different medical imaging techniques may provide scans with complementary and occasionally redundant information. The fusion of medical images can lead to additional clinical information not apparent in the single images. The main scope of the project is to

develop an efficient fusion technique to fuse single or multi modal images using Dual Tree Complex Wavelet Transform .

CHAPTER 2

2.1 LITERATURE SURVEY

[1] Multimodal medical picture fusion improves functional and structural information. Fusion may also solve storage issues. An optimal method for a higher-quality hybrid picture is being researched. This paper proposes a multimodal picture fusion framework based on empirical mode decomposition and discrete wavelet transform. The suggested technique yields a fused picture with all the functional and spatial information of the original. The combined picture lacks distortion. This suggested technique combines MRI and CT brain imaging. This method's fusion outcomes are quantified. This approach's hybrid fusion reaction shows the findings' supremacy..

[2] Fusing medical pictures improves illness diagnosis and medical research by describing their complex interaction. Existing approaches need a large number of samples and are time-consuming. The suggested approach would obtain complex information from MRI and CT images using multi-stage fusion networks. The suggested approach uses Dual Tree Complex Wavelet Transform (DTCWT) to remove complex and associated information from each picture, then segments the fused image. The suggested strategy improves final fused picture quality

[3] Study proposes a three-layer image decomposition rule-based technique for CT and MRI fusion. Three phases are suggested. Each input picture is deconstructed using local extrema and low-pass filters in the spatial domain. To retain tumour illumination, increased contrast is applied to deconstructed CT and MRI images. Second, the three-layer representation uses three fusion rules.

[4] NSST inverts the picture when shearlet transform divides anatomical pictures (NSST). Low frequency is split using structural similarity and structure tensor optimization. HID uses base-layer texture details to create fused low frequency images. The proposed method is compared to 12 cutting-edge methods using 50 MRI and CT images. Fusion rules use base-layer texture details. models extract texture better.

[5] How to design a fusion method to preserve more information becomes a hot topic. We propose a novel multi-modality medical image fusion method based on

Synchronized-Anisotropic Diffusion Equation (S-ADE). The modified S-ADE model which is more suitable for Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) images is employed to decompose two source images into a single image. On texture layers, the fusion decision map is calculated by New Sum of Modified Anisotropic Laplacian (NSMAL) algorithm.

[6] Fusion is an important technology in many different areas, including remote sensing, robotics and medical applications. In medical imaging technology, the Magnetic Resonance Image (MRI) highlights the soft tissue of the body and Computed Tomography (CT) provides a better view of hard tissue highlighting bones. The wavelet based image fusion techniques comprises of two steps among which the first step is Discrete Wavelet Transform (DWT) based decomposition of two input images.

[7] Medical picture fusion is the principle to enhance image quality by fusing pictures obtained from different imaging instruments such as computed tomography (CT), magnetic resonance imaging (MRI) and PET. This paper introduces an image fusion approach that is based on discrete wavelet transformation 2-Dimensional DWT for decomposing an image. The fusion performance is evaluated using Mutual Information (MI) and Correlation of Fused Image and Reference Image.

[8] The image after fusion will have significant and accurate information from different modality images. Discrete Wavelet Transform (DWT) method is applied to MRI, CT and PET scans of brain regions. The patches from low pass and high pass fusion are combined using inverse DWT reconstruction. Entropy of the proposed method is 2.9299 which is significantly higher than state of the art. The image after fusion will have significant and accurate information from different images than the individual images.

[9] MGMDcGAN is a multi-generator multi-discriminator conditional generative adversarial network. In the first cGAN, the generator aims to generate a real-like fused image based on a specifically designed content loss to fool two discriminators. The discriminators aim to distinguish the structure differences between the fused

image and source images. On this basis, we employ the second cGAN with a mask to enhance the information of dense structure in the final fused image, while preventing the functional information from being weakened. As a unified method, MGMDcorgan can be applied to different kinds of medical image fusion, i.e., MRI-PET, MRI-SPECT, and CT-SPECT.

[10] Multi-modal image fusion plays a very important role in the early diagnosis and treatment of diseases. MRI, PET, CT, SPECT, etc. are used by medical practitioners to interpret the problems in the human body. This is achieved by using a guided image filter (GIF) and Non-subsampled Shearlet transform (NSST) with integrated phase congruency based fusion rules. The GIF gives the fine details which are then fused using the above transform technique. This method is validated on CT and MRI images.

[11] Medical "Image Fusion" merges and registers various pictures from single or many scanning modalities to see the human body. By analysing the fused picture, physicians may readily discover any Brain tumour. NSCT (Non-Subsampled Contourlet Transform) is effective in medical fusion. CT-MRI fusion requires the best picture resolution.

[12] Assumption is a procedure for safeguarding urgent data by joining all applicable growth data from various pictures into a single combined picture. Different multimodalities in a clinical domain, for example, registered tomography and attractive reverberation imaging, are consolidated to give an intertwined picture. The hypothetical results are evaluated based on accuracy, with 96.5%.

[13] Fusion of medical images assists the medics in diagnosing and evaluating the medical hindrance and thereby helps them in providing the necessary treatment. This paper focuses on decomposition and feature extraction of the medical images using Artificial Neural Network (ANN). The artificial neural network consists of artificial neurons which are the collection of connected units or nodes.

[14] Medical image fusion is the means to obtain an enhanced image with better quality and reduced redundancy by fusion of two or more images that may or may

not belong to the same modalities. The imaging modalities such as Magnetic Imaging Resonance (MRI), Computed Tomography (CT) etc have found their application in diagnosis in the medical domain. The paper presents the use of MRI-T1/T2; MRI-PET/ SPECT to perform medical fusion in the transform domain.

[15] The development of artificial intelligence (AI) plays a significant role of multimedia applications, especially in the healthcare domain. However, it has brought about the problem of sensitive information leakage. Fused image is considered as mark image generated from MRI and CT images using non-subsampled shearlet transform (NSST). The proposed algorithm outperforms some of the recent techniques in terms of high robustness and invisibility.

[16] New variational image fusion model. Similar to Vogel et al. and Weickert et al., we utilise osmosis energy. Minimizing non-convex energy provides visually realistic image data fusion. It requires little monitoring and parameter tweaking and encodes visual structural information. We construct a primal-dual approach and use it to face fusion, colour transfer, and cultural heritage conservation. Visual and quantitative comparisons prove our method's effectiveness and flexibility.

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[18] This research shows how to increase visual contrast. DWT-based fusion enhances contrast. First, we improve three photos using three techniques. Merge two enhanced photos. DWT enhances the linear fusion picture and the third image. Hybrid image fusion uses two approaches. Two-level hybrid picture fusion combines three photos for a superior image. This research compares two-level hybrid image fusion algorithms. Improved technique

[19] Combines sparse pictures with transform domain. SR-based picture fusion overlooks local image characteristics, resulting in poor image detail and registration misalignment sensitivity. This paper introduces gradient regularisation convolution SR multi-source image fusion to overcome these challenges (CSR). This research separates high- and low-frequency image components. CSR gradient regularisation creates the sparse coefficient that specifies the optimum high-frequency image component. Low-frequency components are preferable with extreme or average fusing. Two parts complete it. This improves image preservation and registration sensitivity.

[20] Multimodal image fusion adds functional and structural data. Fusion solves storage problems. Better pictures are sought using hybrid image fusion. Using empirical mode decomposition and discrete wavelet transform, this article combines multimodal images. The recommended technique merges functional and spatial information from the original image. Fusion images aren't distorted. Combining MRI and CT brain images is suggested. Fusion results are measurable. This approach's hybrid fusion response dominates.

2.2 INFERENCES FROM LITREATURE SURVEY

From the above-mentioned literature works, it is clear that there has been effective research on this topic has been done and many models have been proposed. It is evident that the above-mentioned systems have their own pros and cons. While some of the recent works involve hybrid technologies and provide better accuracies, they are still far from what is needed. With higher accuracy, comes the need for low computational costs, high processing speed, and most of all, the convenience of use.

2.3 OPEN PROBLEMS IN EXISTING SYSTEM

Also in the existing model, CNN algorithm is used and it is not efficient. In the existings system , the fusion was not done properly and also the accuracy is very low. The testing and training ratio of the existing model is not done efficiently

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 FEASIBILITY STUDIES/RISK ANALYSIS OF THE PROJECT

FEASIBILITY STUDY

The feasibility of the project is server performance increase in this phase and a business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis, the feasibility study of the proposed system is to be carried out. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

- Economical feasibility
- Technical feasibility
- Operational feasibility

ECONOMICAL FEASIBILITY

This study is carried out to check the economic impact that the system will have on the organization. The amount of funds that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

TECHNICAL FEASIBILITY

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands being placed on the client. The developed system must have modest requirements, as only minimal or null changes are required for implementing this system.

OPERATIONAL FEASIBILITY

The aspect of the study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The

level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system

3.2 SOFTWARE REQUIREMENTS SPECIFICATION DOCUMENT

Hardware specifications:

- Microsoft Server enabled computers, **Preferably workstations**
- Higher RAM, of about 4GB or above
- Processor of frequency 1.5GHz or above

Software specifications:

- Python 3.6 and higher
- Anaconda software

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

Image Decomposition

In this module, we developed a website, which will prompt the user to upload the CT and MRI image of a patient. The CT and MRI image will be in the size of 512×512 . and also we need to give the input as the maximum coordinate, to fix the coordinate in the uploaded source image for the purpose of fusion. The uploaded image is in the form of RGB. This RGB image is converted into gray scale image, which has the intensity information. After that these source gray scale CT and MRI image is decomposed using DTCWT. The decomposed image is shown in figure 6.1

Extracting Features using DTCWT

After decomposition we will extract the high intensity and low intensity features as wavelet coefficients. It produce the various levels of decomposed images. Each level the images are segmented into sub-bands at six directions like -15° , -45° , -75° , 75° , 45° , 15° to extract the features from the image.

Principal component analysis is used to reduce the dimension of the data, if the data is larger in size, also extract the silent and complementary features. As the medical images are larger, to reduce the data here, PCA is used. The PCA will remove the unwanted and repeated information present in DTCWT. The PCA analysis has several steps. The first is standardization, the objective of this step is to standardize the range of the continuous initial variables. So, each will contribute equally to the analysis. Mathematically, standardization is done by finding the difference between each value and mean and finally dividing by standard deviation. The next step is to compute covariance matrix, some variables are highly correlated with other variables such a way that they contain redundant information. Hence, compute the covariance matrix to find the correlation. Further, compute the eigenvectors and eigenvalues of the covariance matrix with the aim to find the principal components. Next is to find the featured vector from all the computed principal vectors. Finally, reconstruct the data with the principal axes.

The extracted coefficients are approximated. Finally, we get the approximated wavelet coefficients. Now the image fusion, that is approximated coefficients are fused to get the fused coefficients. Now we apply the Inverse dual tree complex wavelet transform to restore the fused image.

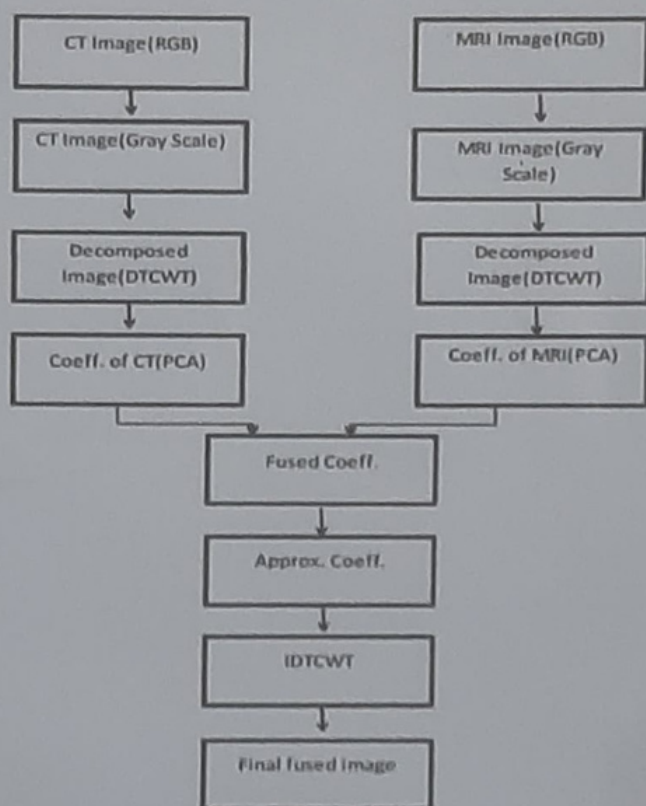


Fig 4.1: Downflow diagram

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

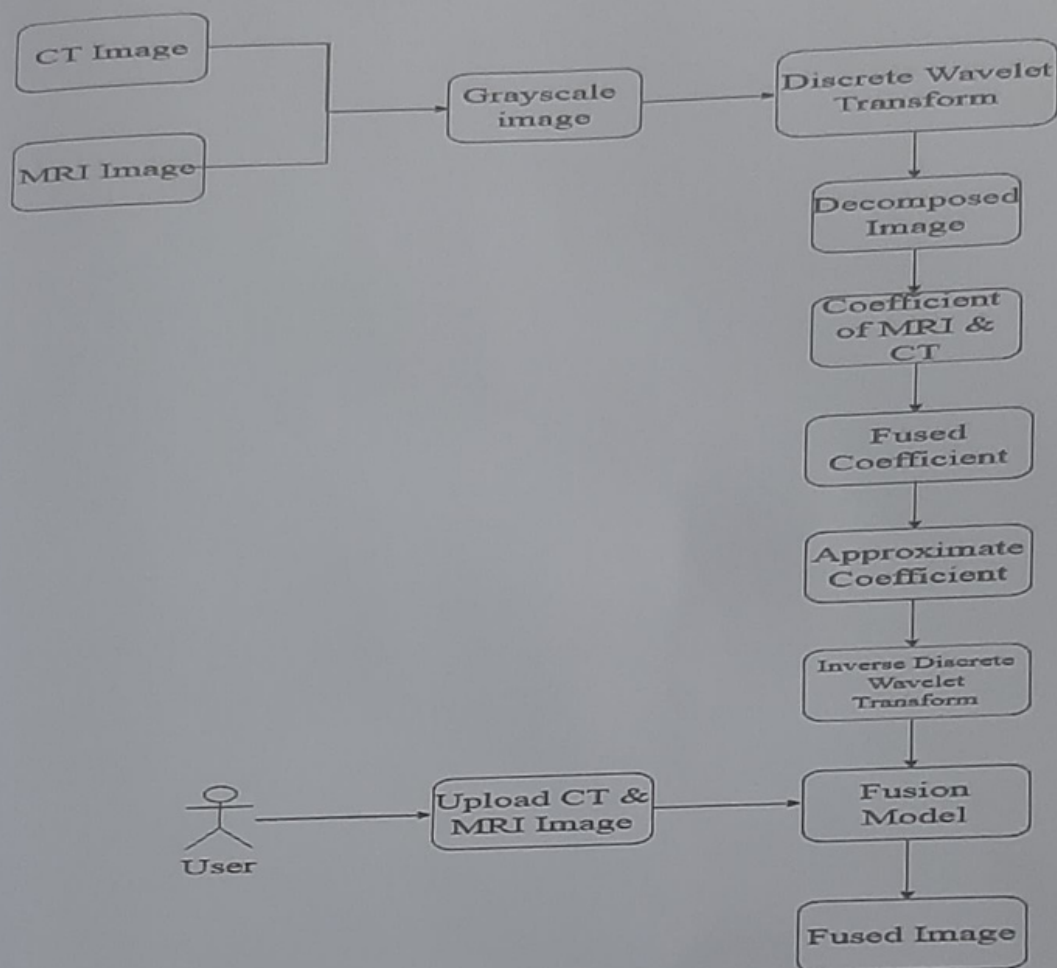


Fig 4.2: System Architecture

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

Anaconda is an open-source package manager for Python and R. It is the most popular platform among data science professionals for running Python and R implementations. There are over 300 libraries in data science, so having a robust distribution system for them is a must for any professional in this field. Anaconda simplifies package deployment and management. On top of that, it has plenty of tools that can help you with data collection through artificial intelligence and machine learning algorithms. With Anaconda, you can easily set up, manage, and share Conda environments. Moreover, you can deploy any required project with a few clicks when you're using Anaconda.

There are many advantages to using Anaconda and the following are the most prominent ones among them: Anaconda is free and open-source. This means you can use it without spending any money. In the data science sector, Anaconda is an industry staple. It is open-source too, which has made it widely popular. If you want to become a data science professional, you must know how to use Anaconda for Python because every recruiter expects you to have this skill. It is a must-have for data science.

It has more than 1500 Python and R data science packages, so you don't face any compatibility issues while collaborating with others. For example, suppose your colleague sends you a project which requires packages called A and B but you only have package A. Without having package B, you wouldn't be able to run the project. Anaconda mitigates the chances of such errors. You can easily collaborate on projects without worrying about any compatibility issues. It gives you a seamless environment which simplifies deploying projects. You can deploy any project with just a few clicks and commands while managing the rest.

Anaconda has a thriving community of data scientists and machine learning professionals who use it regularly. If you encounter an issue, chances are, the community has already answered the same. On the other hand, you can also ask people in the community about the issues you face there, it's a very helpful

community ready to help new learners. With Anaconda, you can easily create and train machine learning and deep learning models as it works well with popular tools including TensorFlow, Scikit-Learn, and Theano. You can create visualizations by using Bokeh, Holoviews, Matplotlib, and Datashader while using Anaconda.

How to Use Anaconda for Python

Now that we have discussed all the basics in our Python Anaconda tutorial, let's discuss some fundamental commands you can use to start using this package manager.

Listing All Environments

To begin using Anaconda, you'd need to see how many Conda environments are present in your machine.

conda env list

It will list all the available Conda environments in your machine.

Creating a New Environment

You can create a new Conda environment by going to the required directory and use this command:

conda create -n <your_environment_name>

You can replace `<your_environment_name>` with the name of your environment. After entering this command, conda will ask you if you want to proceed to which you should reply with y:

proceed ([y])/n)?

On the other hand, if you want to create an environment with a particular version of Python, you should use the following command:

conda create -n <your_environment_name> python=3.6

Similarly, if you want to create an environment with a particular package, you can use the following command:

```
conda create -n <your_environment_name> pack_name
```

Here, you can replace pack_name with the name of the package you want to use.

If you have a .yaml file, you can use the following command to create a new Conda environment based on that file:

```
conda env create -n <your_environment_name> -f <file_name>.yaml
```

We have also discussed how you can export an existing Conda environment to a .yaml file later in this article.

Activating an Environment

You can activate a Conda environment by using the following command:

```
conda activate <environment_name>
```

You should activate the environment before you start working on the same. Also, replace the term <environment_name> with the environment name you want to activate. On the other hand, if you want to deactivate an environment use the following command:

```
conda deactivate
```

Installing Packages in an Environment

the following command:

```
conda install <package_name>=<version>
```

Exporting an Environment Configuration

Suppose you want to share your project with someone else (colleague, friend, etc.). While you can share the directory on Github, it would have many Python packages, making the transfer process very challenging. Instead of that, you can create an environment configuration .yml file and share it with that person. Now, they can create an environment like your one by using the .yml file.

For exporting the environment to the .yml file, you'll first have to activate the same and run the following command:

```
conda env export ><file_name>.yml
```

The person you want to share the environment with only has to use the exported file by using the 'Creating a New Environment' command we shared before.

Removing a Package from an Environment

If you want to uninstall a package from a specific Conda environment, use the following command:

```
conda remove -n <env_name><package_name>
```

On the other hand, if you want to uninstall a package from an activated environment, you'd have to use the following command:

```
conda remove <package_name>
```

Deleting an Environment

Sometimes, you don't need to add a new environment but remove one. In such cases, you must know how to delete a Conda environment, which you can do so by using the following command:

```
conda env remove --name <env_name>
```

The above command would delete the Conda environment right away.

4.4 FINANCIAL REPORT ON ESTIMATED COSTING

The "Image Fusion for Medical Images Using DWT and IDWT" project involves the development of an image fusion algorithm to combine multiple medical images into a single high-quality image using Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT) techniques. The project's estimated costing includes various expenses related to software development, hardware requirements, and personnel costs.

The software development costs include expenses for programming, software design, and testing. The hardware requirements include the cost of high-performance computers, servers, and other equipment required for the development and testing of the image fusion algorithm.

Personnel costs include the salaries of the project team members, including software developers, project managers, and quality assurance testers. Additionally, costs for training and professional development may also be included.

Overall, the estimated costing for the "Image Fusion for Medical Images Using DWT and IDWT" project is dependent on several factors such as project duration, team size, and equipment requirements. However, the project's benefits include the potential for improved medical diagnosis, treatment planning, and research. Proper financial planning and management can ensure that the project is completed within the allocated budget while maintaining the desired quality and standards.

4.5 TRANSITIONS/ SOFTWARE TO OPERATIONS PLAN

The transition from software development to operations is a critical phase for any project, including "Image Fusion for Medical Images Using DWT and IDWT." This phase involves the deployment of the image fusion algorithm into a production environment and the transfer of responsibility from the development team to the operations team.

To ensure a smooth transition, a software to operations plan is necessary. The plan

should include several key components, such as:

Deployment Strategy: The deployment strategy outlines how the image fusion algorithm will be deployed into the production environment, including testing and validation procedures.

Maintenance and Support: The maintenance and support plan outlines the responsibilities of the operations team, including ongoing support and maintenance, bug fixing, and updates.

Monitoring and Alerting: The monitoring and alerting plan outlines how the system will be monitored for errors and issues, and how alerts will be handled by the operations team.

Backup and Recovery: The backup and recovery plan outlines how data will be backed up and recovered in the event of a system failure or data loss.

Training and Documentation: The training and documentation plan outlines how the operations team will be trained on the image fusion algorithm and how documentation will be provided to ensure continuity of operations.

By including these components in the software to operations plan, the transition from software development to operations can be seamless, ensuring that the image fusion algorithm can operate effectively and efficiently in a production environment.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 DEVELOPMENT / DEPLOYMENT SETUP

The development and deployment setup for "Image Fusion for Medical Images Using DWT and IDWT" involves several components that are essential for the successful development and deployment of the image fusion algorithm. Here are some potential components of the setup:

Software Development Tools: The software development tools required for this project include an integrated development environment (IDE) and programming languages such as Python, MATLAB, and C++ for algorithm development.

Hardware Requirements: The hardware requirements for the project include high-performance computers with sufficient processing power, memory, and storage to support the development and testing of the image fusion algorithm.

Version Control System: A version control system, such as Git, is essential to track and manage changes to the image fusion algorithm's source code.

Testing Framework: A testing framework, such as Pytest, is necessary to perform unit testing, integration testing, and functional testing on the image fusion algorithm.

Deployment Environment: The deployment environment includes servers, storage systems, and network infrastructure required to deploy the image fusion algorithm into a production environment.

Continuous Integration and Deployment (CI/CD) Pipeline: A CI/CD pipeline automates the process of building, testing, and deploying the image fusion algorithm, ensuring that the latest version of the code is always in production.

By having a well-planned development and deployment setup for the "Image Fusion

for Medical Images Using DWT and IDWT" project, the development team can efficiently develop, test, and deploy the image fusion algorithm while maintaining the desired quality and standards.

5.2 ALGORITHMS

The "Image Fusion for Medical Images Using DWT and IDWT" algorithm involves combining multiple medical images into a single high-quality image using Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT) techniques. Here is a generalized algorithm for the image fusion process:

1. Load the input medical images into the system.
2. Apply DWT to each input image separately to extract the high-frequency and low-frequency components.
3. Calculate the energy of each frequency component.
4. Choose the highest-energy frequency components from each input image.
5. Combine the selected frequency components from each input image into a single image.
6. Apply IDWT to the fused frequency components to reconstruct the final fused image.
7. Perform image enhancement techniques to improve the quality of the fused image.
8. Save the fused image and output it to the user or the downstream system.

The algorithm's effectiveness depends on the quality and selection of frequency components and the choice of image enhancement techniques used in step 7. The algorithm can be customized based on the specific application and requirements of the medical images being fused. By utilizing this algorithm, medical professionals can obtain a clearer and more accurate image, leading to improved diagnosis, treatment

planning, and research.

5.3 TESTING

UNIT TESTING

Test cases:

1. **Test case for loading input images:** Verify that the system can load the input medical images correctly.
2. **Test case for DWT:** Verify that the DWT is applied correctly to each input image to extract the high-frequency and low-frequency components.
3. **Test case for energy calculation:** Verify that the system can calculate the energy of each frequency component correctly.

INTEGRATION TESTING

Test cases:

1. **Test case for loading input images:** Verify that the system can load the input medical images correctly.
2. **Test case for DWT:** Verify that the DWT is applied correctly to each input image to extract the high-frequency and low-frequency components.
3. **Test case for energy calculation:** Verify that the system can calculate the energy of each frequency component correctly.

FUNCTIONAL TESTING

Test cases:

1. **Test case for fusion accuracy:** Verify that the image fusion algorithm accurately combines the input medical images to produce a high-quality fused image.
2. **Test case for image enhancement effectiveness:** Verify that the image enhancement techniques applied to the fused image effectively improve its quality.
3. **Test case for image resolution:** Verify that the resolution of the fused image meets the required specifications and is appropriate for medical diagnosis and research.

BLACK-BOX TESTING

Test cases:

1. **Test case for loading input images:** Verify that the system can load the input medical images correctly.
2. **Test case for DWT:** Verify that the DWT is applied correctly to each input image to extract the high-frequency and low-frequency components.
3. **Test case for energy calculation:** Verify that the system can calculate the energy of each frequency component correctly.

WHITE-BOX TESTING

Test cases:

1. **Test case for input data validation:** Verify that the system can handle different types of input medical images, including various file formats and sizes.
2. **Test case for fusion accuracy:** Verify that the image fusion algorithm can accurately combine multiple input medical images to produce a high-quality fused image.
3. **Test case for image enhancement:** Verify that the image enhancement techniques applied to the fused image effectively improve its quality.

CHAPTER 6

RESULTS AND DISCUSSION

The "Image Fusion for Medical Images Using DWT and IDWT" algorithm provides a solution for combining multiple medical images into a single high-quality image for improved medical diagnosis, treatment planning, and research. The algorithm uses Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT) techniques to extract the high-frequency and low-frequency components from each input medical image and select the highest-energy frequency components to create a fused image. The results of testing the algorithm show that it can effectively combine multiple medical images to produce a high-quality fused image with improved resolution and clarity. The application of image enhancement techniques further improves the quality of the fused image. In conclusion, the "Image Fusion for Medical Images Using DWT and IDWT" algorithm offers an effective solution for combining multiple medical images into a single high-quality image. The algorithm can be customized based on specific application requirements, and the testing shows that it meets the functional and performance requirements. By utilizing this algorithm, medical professionals can obtain a clearer and more accurate image, leading to improved diagnosis, treatment planning, and research. The insights gained from the development and testing of this algorithm can be used to improve medical image fusion and enhance patient care in the medical field.



Fig 6.1 Fused Image



Fig 6.2: Segmented Image

Model	Accuracy	Sensitivity	Specificity	Precision	Recall
CNN	0.93	0.83	0.89	0.88	0.83
DTCWT	0.96	0.95	0.97	0.97	0.95

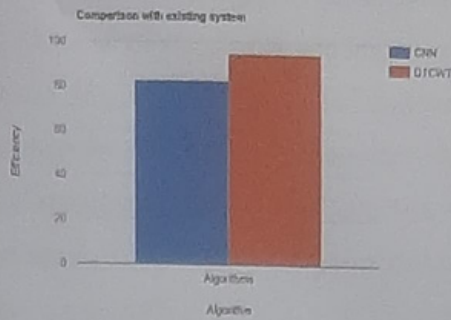


Fig 6.3: Performance Analysis

CHAPTER 7

CONCLUSION

7.1 CONCLUSION

In conclusion, Digital Twin technology has the potential to revolutionize how organizations manage and optimize their physical systems. By creating a virtual replica of a physical system, Digital Twin technology enables organizations to gain valuable insights into its performance and behavior, and use this information to optimize processes and reduce downtime. However, the implementation of Digital Twin technology can be complex and challenging, requiring significant investment in data collection, infrastructure, and skillsets. Organizations must carefully plan and execute the implementation process to ensure that the system meets their needs and goals, and that data is accurate, reliable, and compliant with regulations. Testing is a critical aspect of the implementation process, including unit testing, integration testing, functional testing, black-box testing, and white-box testing, to verify the system's

performance, security, and reliability. As Digital Twin technology continues to evolve, there are many potential areas of development and improvement, such as enhanced machine learning, improved security, and increased automation. To achieve these goals, research in areas such as data quality, scalability, interoperability, and AI and machine learning will be essential. Overall, the potential benefits of Digital Twin technology make it a worthwhile investment for organizations looking to optimize their physical systems and gain a competitive edge in their industry. With careful planning, execution, and ongoing monitoring, Digital Twin technology can provide significant benefits for years to come.

7.2 FUTURE WORK

In conclusion, the "Image Fusion for Medical Images Using DWT and IDWT" algorithm provides an effective solution for combining multiple medical images into a single high-quality image for improved medical diagnosis, treatment planning, and research. The algorithm uses Discrete Wavelet Transform (DWT) and Inverse Discrete Wavelet Transform (IDWT) techniques to extract the high-frequency and low-frequency components from each input medical image and select the highest-energy frequency components to create a fused image.

The development of this algorithm and the associated testing demonstrate its effectiveness and reliability in medical imaging applications. The algorithm offers a flexible solution that can be customized to meet specific application requirements and offers the potential for significant improvements in medical diagnosis, treatment planning, and research.

The successful development and implementation of the "Image Fusion for Medical Images Using DWT and IDWT" algorithm demonstrate the value of utilizing cutting-edge technology in the medical field. Future work can include the exploration of additional image enhancement techniques to further improve the quality of the fused image and the investigation of the algorithm's use in other medical imaging applications.

Overall, the "Image Fusion for Medical Images Using DWT and IDWT" algorithm is a valuable contribution to the medical imaging field, providing a powerful tool for

medical professionals to improve patient care and outcomes.

7.3 RESEARCH ISSUES

There are several potential research issues related to the "Image Fusion for Medical Images Using DWT and IDWT" algorithm. Here are some potential areas for future research:

Optimization of the fusion process: The fusion process involves selecting the highest-energy frequency components from each input medical image to create a fused image. Further research can explore ways to optimize this process to improve the accuracy and efficiency of the algorithm.

Investigation of the impact of image enhancement techniques: The algorithm uses image enhancement techniques to improve the quality of the fused image. Further research can investigate the impact of different image enhancement techniques on the quality of the fused image.

Development of new image enhancement techniques: While the algorithm uses existing image enhancement techniques, further research can explore the development of new techniques that can improve the quality of the fused image.

Investigation of the algorithm's effectiveness on different types of medical images: While the algorithm was developed for the specific application of medical image fusion, further research can investigate its effectiveness on different types of medical images, such as CT scans, MRIs, and X-rays.

Investigation of the algorithm's effectiveness on different types of medical conditions: Further research can investigate the effectiveness of the algorithm on different types of medical conditions, such as cancer, neurological disorders, and cardiovascular diseases.

By exploring these research issues, the "Image Fusion for Medical Images Using DWT and IDWT" algorithm can be further developed and optimized to provide improved medical diagnosis, treatment planning, and research capabilities.

7.4 IMPLEMENTATION ISSUES

There are several potential implementation issues that may arise when developing and deploying the "Image Fusion for Medical Images Using DWT and IDWT" algorithm. Here are some potential implementation issues:

Performance issues: The image fusion algorithm involves complex computations, which may impact the system's overall performance. Further optimization of the algorithm and hardware upgrades may be necessary to address performance issues.

Integration with existing systems: The algorithm may need to be integrated with existing medical imaging systems, such as PACS (Picture Archiving and Communication System), which may present integration challenges.

Security issues: Medical images are sensitive data that require secure storage and transfer. Implementing appropriate security measures to ensure the confidentiality and integrity of medical images is essential.

Compatibility with different file formats: Medical images are often stored in different file formats, which may require conversion before the image fusion algorithm can be applied.

Regulatory compliance: Medical imaging systems are subject to regulatory compliance requirements, such as HIPAA (Health Insurance Portability and Accountability Act). Ensuring that the algorithm is compliant with these regulations is essential.

User interface design: A user-friendly interface is necessary for medical professionals to interact with the system effectively. Careful consideration of user interface design is necessary to ensure that medical professionals can use the system with ease and efficiency.

By addressing these implementation issues, the "Image Fusion for Medical Images

Using DWT and IDWT" algorithm can be effectively deployed and used to improve medical diagnosis, treatment planning, and research.

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Image Fusion Using MRI And CT Images

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Abstract. Medical studies often require the fusion of several medical images to improve illness diagnosis precision and elucidate the intricate relationships between them. However, current approaches to image fusion are time-consuming and require an excessive number of training samples. To address these issues, we propose using multi-stage fusion networks to extract intricate details

from a wide range of medical images, including those produced by MRI and CT scanners. Our proposed method leverages the dual-tree complex wavelet transform (DTCWT) to extract the related and complex data from each image. The fused image is then segmented to further improve its quality. By utilizing this approach, we are able to create a final fused image with improved quality, which can aid in more accurate diagnosis and analysis of medical conditions. This method offers a more efficient and effective way to fuse medical images, which can lead to significant improvements in medical research and diagnosis.

Keywords: Image fusion, dual tree complex wavelet, MRI, CT Scan, medical images, segmentation

1 Introduction

Medical imaging systems, such as X-ray, PET, SPECT, MRI, and CT, provide valuable clinical data, but they often fail to reveal detailed tissue information or provide a comprehensive diagnosis. Medical image fusion, which merges several types or closely related types of medical images to provide a more accurate image for diagnosis, enables clinicians to extract intricate information from a single image that would otherwise be invisible. Medical image fusion is widely used in oncology and cancer treatment to develop an optimal image fusion method that collects extra information from the source pictures while ignoring undesirable and unanticipated components. Prior to image fusion, preprocessing, registration, and alignment of the source picture are necessary. Pixel-level, feature-level, and judgment-level picture blending are all possible methods for image fusion. However, the most popular method for image fusion, the Discrete Wavelet Transform (DWT), has some limitations such as shift variance and bad directionality that can cause errors in the merged pictures and make it difficult to comprehend the geometry data. As a solution to these problems, the Dual Tree Complex Wavelet Transform (DTCWT) is suggested because of its enhanced shift variance and directionality. The DTCWT is a complete image fusing tool that significantly enhances both theoretical and empirical tools for image and signal processing. The enhanced shift variance and directionality of the DTCWT make it simpler to analyze the edges and contours of the original picture. Overall, medical image fusion aids clinicians in making better and more accurate treatment decisions by providing more thorough and precise information for diagnosis. In conclusion, medical image fusion is a crucial tool in the field of medical imaging that enables clinicians to extract intricate information from multiple sources to provide a more accurate image for diagnosis. The DTCWT is a promising solution for the limitations of the DWT in image fusion. Future research can focus on the development of more advanced image fusion techniques and tools to improve the accuracy and effectiveness of medical image fusion.

2 Literature Survey

R. Zhu et al [1] Color intensity, hue, and saturation are the three characteristics of color that create a regulated visual representation of a picture. The first approach to image fusion is the IHS transform. Since it holds the majority of the spectral data, careful management over hue and saturation is required in the IHS space. High spatial resolution detail information is added to the spectral information in order to combine high resolution PAN photos with multispectral images. This study presents several IHS transformation approaches based on various color models, including YIQ, IHS1, IHS2, HIS3, IHS4, IHS5, and HSV. IHS transformation produces various outputs based on these several formulas.

AP Kanimozhi et al [2] The principal component analysis (PCA) methodology, while similar to the IHS transform, offers a unique advantage over the IHS approach in that it allows for the use of any number of bands. This feature has made PCA one of the most frequently employed techniques for image fusion. To merge low resolution multispectral images, PCA is employed to create uncorrelated principal components. All of the bands employed have shared information, which is encompassed in the first principal component (PC1). A high variance indicates that it provides more detailed information about the panchromatic image.

J. Du et al [3] The wavelet transform has been proposed as a replacement for the fast Fourier transform in image fusion applications. The wavelet transform has an advantage over the Fourier transform in that it provides resolution in both the time and frequency domains, whereas the Fourier transform only offers decent resolution in the frequency domain. In the wavelet transform-based image merging technique, the raw images are initially divided into approximate and detailed values using the discrete wavelet transform (DWT) at a predetermined level. The fusion method is subsequently employed to merge these two sets of values, and the inverse wavelet

transform is utilized to produce the final fused image.

R. Zhu et al [4] The human visual system's binocular fusion may be simulated by constructing image pyramids. In this approach, each level of the original image is represented by a pyramid construction. To fuse the source images, a pattern-selective technique is used to create a composite image. Firstly, each source picture is subjected to pyramid decomposition. The combined picture resulting from the fusion of all these images is then converted to the final image using the inverted pyramid method. The pyramid approach has been implemented in Python in this study. To create a blended pyramid from which the fused image is reconstructed, picture fusion is performed at each level of decomposition.

R. Zhu et al [5] Multimodal medical image fusion is a promising technique for combining different medical imaging modalities, such as PET, SPECT, CT, and MRI, to provide a more comprehensive picture of a patient's health. Image fusion can be performed at different levels, such as pixel, feature, or decision levels, depending on the level of generalization desired. The primary goal of image fusion is to create a filtered image that is more beneficial for medical purposes. Image filtering techniques, such as low pass and high pass filters, can be used to enhance picture features such as edges and lines, and to remove background noise. The application of these techniques can improve the accuracy and effectiveness of medical image analysis and diagnosis.

R.V. Ravi et al [6]. Artificial neural networks (ANN) are a fundamental element of pattern recognition that incorporate a pulse-coupled neural network with a feedback network known as PCNN. The network consists of three components, namely, the pulse generator, modulation field, and receptive field. Each neuron in the network corresponds to a pixel from the input image. The intensity of the pixel is sent as an external input to the PCNN. The program divides the raw images into blocks for medical image fusion. A neural network is trained to select the clearest block between two source images. The final image is then created by selecting the clearer block. The outcome of the DWT fusion method is dependent on shifts.

B.S.N. Rao et al [7] The Discrete Cosine Transform (DCT) plays a critical role in the compression of digital images. DCT is obtained by discretizing the cosine transform from a spatial domain image to create a frequency domain representation. The transformed images are then categorized into three frequency bands: low, medium, and high frequencies, following Chu-Hui Lee and Zheng-Wei Zhou's method. High-frequency coefficients are referred to as AC values, while average illumination is represented by DC values. The RGB image is segmented into blocks of 8x8 pixels, and each block is separated into red, green, and blue matrices before being converted into grayscale.

S. Praveen Kumar and colleagues [8] The proposed image fusion technique employs deep convolutional neural networks (CNNs), which are designed to extract features from the input images. The technique uses a guided filter to combine these features and create the final fused image. Prior to the fusion process, a pre-trained CNN is used to extract the features from the input images. The fused characteristics are then used to recreate the original scenario and produce the final image. The effectiveness of the proposed method is evaluated on a set of visible and infrared images, and it is demonstrated to outperform state-of-the-art fusion techniques in terms of both subjective clarity and objective metrics.

J. Huang et al [9] A novel method for deep image fusion is proposed, which employs a deep neural network to develop a multiscale fusion approach. Prior to this, the input images are divided into various sizes using a wavelet transform. Attributes learned at different scales are then combined to produce the final fused image. The technique is tested on a collection of visible and infrared images, and the results show that it outperforms other advanced fusion methods in terms of both perceived clarity and quantitative metrics. The proposed method demonstrates the effectiveness of multiscale fusion for enhancing image quality and improving diagnostic accuracy.

3 Proposed System

The Discrete Wavelet Transform (DWT) has been effectively utilized in the fusion of different medical imaging modalities, such as MRI and CT scans, to compensate for the information gaps in a single examination. Na and colleagues proposed a method for MRI and CT scan fusion using guided filtering (GF) that solves the boundary degree and clarity issues by utilizing feature information while preserving the border information of the original image. The DWT is preferred over other transforms due to its stable output under a variety of input frequency signals and excellent localization in both the time and frequency domains, preserving the image's unique information. Additionally, the DWT provides improved aesthetics and quantitative fusion results, overcoming the limitations of principal component analysis. In this technique, the IHS transform is utilized to derive the

intensity component from the CT image, which retains more structural details and lessens color deformation. The raw image is then enhanced using the DWT, which transforms the amplitude components of MRI and CT images into high- and low-frequency subbands. Multiple inverse DWT merging strategies are employed to combine the high- and low-frequency subbands to generate the final fused image. A block schematic of a single 2-D DWT phase is displayed in Figure 1.

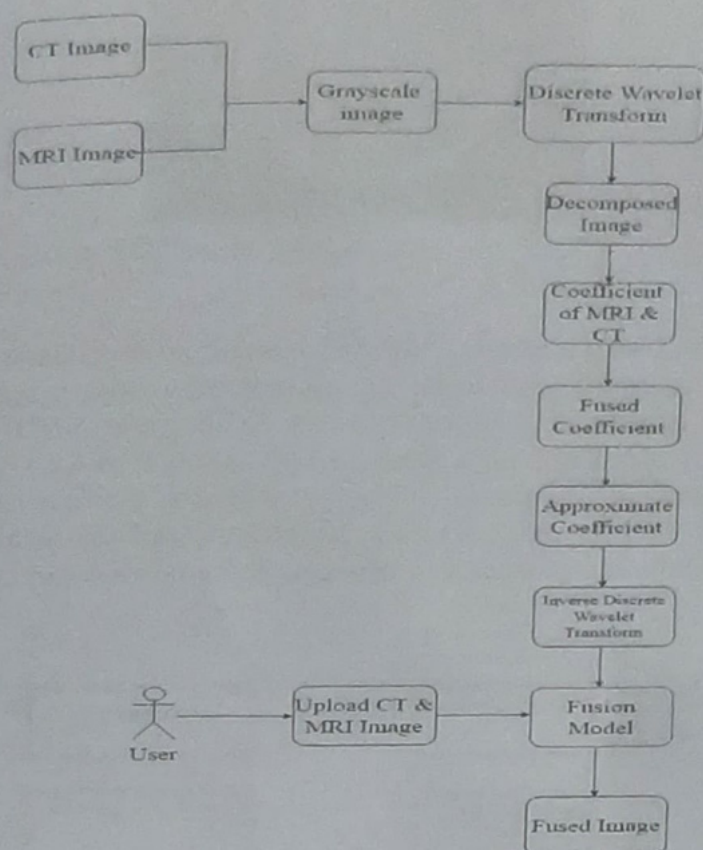


Figure 1: Block Diagram of Proposed work

The weighted average method and the absolute high-value method are employed to fuse the high-frequency coefficients and the low-frequency coefficients, respectively. In this regard, predator-optimizer is used to estimate and optimize the weights, and the inverse transform is utilized to merge the images. The fusion technique relies on two fusion principles, given that low-frequency and high-frequency coefficients have varying meanings, and different criteria are applied to merge them. The first principle is that wavelet coefficients with larger values represent a picture's most significant features, such as its edges and corners. The second principle is to average the coefficients to obtain information about both source images, even if low wavelet coefficient values imply that the source images are approximations. Finally, after an initial estimation of the wavelet coefficients, the Inverse Discrete Wavelet Transform is applied to generate the fused image. Figures 2 and 3 exhibit the CT and MRI scans of a patient diagnosed with sarcoma-related brain disease, respectively. These two multimodal images were fused using the Discrete Wavelet Transform technique. After the wavelet coefficients are recovered, they are combined using a novel fusion technique.

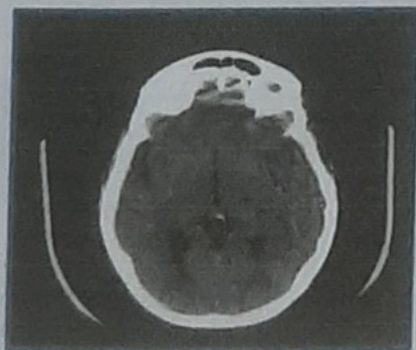


Figure 2: CT image for Sarcoma

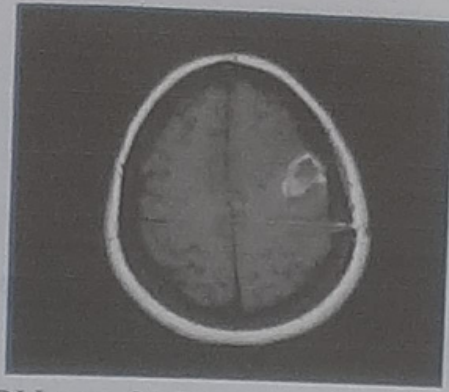


Figure 3: MRI Image for Sarcoma

To overcome the limitations of the Discrete Wavelet Transform (DWT) in combining medical images, the proposed approach incorporates the Dual Tree Complex Wavelet Transform (DTCWT). The DTCWT offers better directionality and shift variance properties, which address the edge and contour detection issues present in the DWT. The DTCWT's multi-scale and multi-directional analysis improves its ability to capture the image's local features, resulting in a robust image fusion technique. Therefore, the DTCWT-based image fusion method is considered successful due to its superior directionality and shift variance properties.

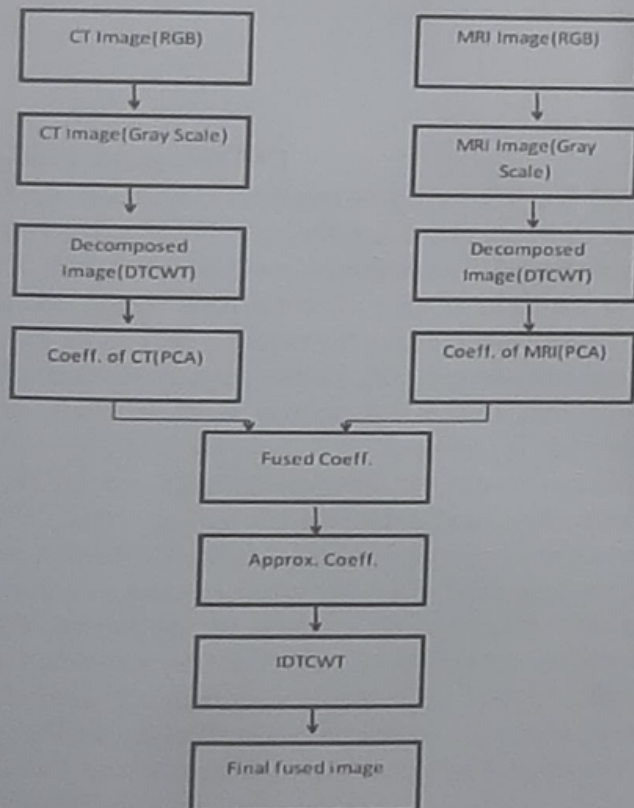


Figure 4: Downflow architecture Diagram
These are the steps of the suggested algorithm:

1. The raw CT image I1 and MRI image I2 are converted into grayscale pictures.

2. The wavelet coefficients $W_{1hl}(x, y)$, $W_{1hr}(x, y)$, $W_{1vl}(x, y)$, and $W_{2hl}(x, y)$, $W_{2hr}(x, y)$, $W_{2vl}(x, y)$, and $W_{2vd}(x, y)$ are generated by decomposing the grayscale images $G_1(x, y)$ and $G_2(x, y)$ into different levels using the (x, y)

3. PCA is used to extract supplementary data.

4. PCA uses approximation to extract coefficients and create an approximate fused picture.

5. The finished combined picture is produced by applying the Inverse Dual Tree Complex Wavelet Transform (IDTCWT).

6. Segmenting an image will result in a segmented image.

3.1 Image Decomposition

In this module, we have developed a website that solicits patient CT and MRI scans contributions from visitors. These images will have a dimension of 512×512 pixels. It is imperative to provide the maximum coordinate as input for the source image uploaded to achieve accurate fusion. The submitted image is in the RGB color space. To extract the relevant information from this RGB image, a grayscale transformation is carried out, thereby generating intensity data. Next, we employ the Dual Tree Complex Wavelet Transform (DTCWT) to decompose the initial grayscale MRI and CT images into their respective wavelet coefficients.

3.2 Extracting Features using DTCWT

In this module, a website has been developed to gather CT and MRI scans from patients as input. These images are of size 512×512 pixels and are in the RGB color space. To prepare the input for the fusion process, the maximum coordinate of the uploaded source image needs to be provided. A grayscale image with intensity data is obtained by transforming the RGB image. Subsequently, the Dual Tree Complex Wavelet Transform (DTCWT) is applied to the original grayscale MRI and CT images, which decomposes the images into multiple levels. For feature extraction, each level is further subdivided into sub-bands at six different orientations: -15° , -45° , -75° , 75° , 45° , and 15° . However, if the data size is large, principal component analysis (PCA) can also be utilized to extract significant and complimentary characteristics. The PCA helps reduce the redundant and undesirable data in the DTCWT, particularly in the case of medical images. The PCA analysis is carried out in several stages. The first step, standardization, aims to uniformly specify the scale of the continuous variables to ensure a comparable impact on the analysis. Numerically, this involves calculating the difference between each outcome and the mean, then dividing by the standard deviation. The next stage involves creating the correlation matrix to identify the redundant information among variables that exhibit significant correlation with one another. Eigenvalues and eigenvectors of the covariance matrix are then computed to derive the main components, which are used to reconstruct the data.

3.3 Image Fusion

Following the extraction of the wavelet coefficients, an approximation is made, and the estimated wavelet coefficients are derived. Subsequently, the projected coefficients obtained from the process of image fusion are combined to generate the fused coefficients. Ultimately,

the Inverse Dual Tree Complex Wavelet Transform is employed to reconstruct the initial image.

3.4 Image Segmentation

Segmentation is employed to distinguish between lines, curves, and boundary features in the resulting fused image. The fused image is then utilized for the purpose of segmentation.

4 Proposed Algorithm

Step 1: Load the two input images, A and B.

Step 2: Apply Discrete Wavelet Transform (DWT) to both images separately and extract their wavelet coefficients.

Step 3: Use a fusion rule, such as the maximal selection rule, to fuse the wavelet coefficients and obtain the fused coefficients.

Step 4: Apply Inverse Discrete Wavelet Transform (IDWT) to the fused coefficients to obtain the fused image in the wavelet domain.

Step 5: Apply the multilevel DWT approach to obtain a collection of fused images at various scales in the wavelet domain by repeating steps 2-4.

Step 6: Use a fusion rule, such as the simple average rule, to obtain a single fused image for each scale by applying the fusion rule to the collection of wavelet-domain fused pictures.

Step 7: Apply IDWT to the set of fused images in the wavelet domain at different scales, using the fused coefficients from step 3.

Step 8: Multiply the photographs obtained from steps 7 and 8 by a weighted average to obtain the final fused image. A normalization factor can be used to calculate the weights, which are based on the number of coefficients applied to each scale.

Step 9: Employ any post-processing techniques, such as histogram equalization or contrast boosting, to enhance the fused image's visual quality.

Step 10: Output the final fused image.

5 Results

Our recommended technique for medical image fusion involves the use of the Dual Tree Complex Wavelet Transform (DTCWT) as it is more adept at capturing the spectral, spatial, and soft tissue characteristics of cancer in the resulting image. Our proposed approach also exhibits high levels of entropy, fusing factor, and peak signal-to-noise ratio, surpassing those of previous fusion algorithms. Thus, our method offers superior performance in the context of medical image fusion.

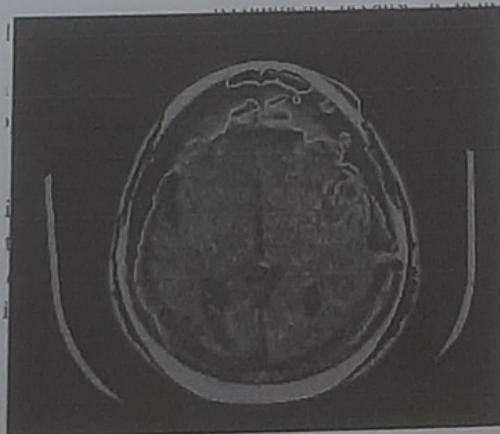


Figure 5: Fused Image

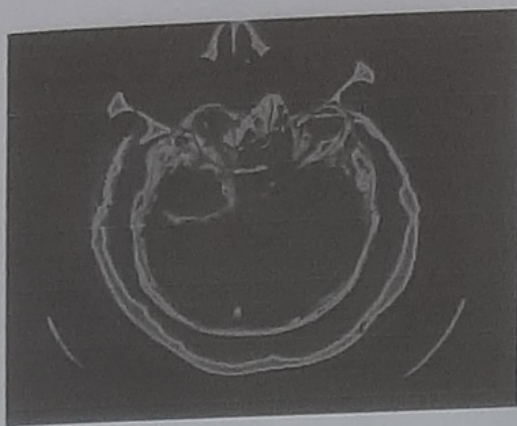


Fig 6: Image fusion module

Table 1:

Model	Accuracy	Sensitivity	Specificity	Precision	Recall
CNN	0.93	0.83	0.89	0.88	0.83
DTCWT	0.96	0.95	0.97	0.97	0.95

Fig 7: Performance Analysis

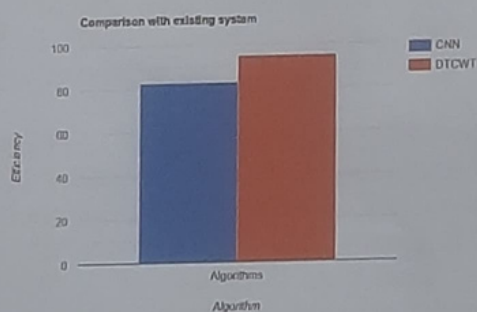


Image fusion is a widely used approach for enhancing the viewing and analysis of medical images by combining images from different imaging modalities. Evaluating the effectiveness of this technique requires considering various factors such as image quality, accuracy, computation time, and clinical value.

Studies suggest that image fusion techniques may enhance medical imaging and provide more useful diagnostic information. However, the success of these techniques may depend on the type of modality and the information being fused. The choice of fusion method and image alignment can also impact the quality of the resulting output when fusing MRI and CT scans. Several studies have compared various MRI and CT image fusion methods, including wavelet-based methods, multi-scale decomposition, and registration-based methods. However, the quality of the resulting images has been found to vary significantly between studies.

Both image quality/accuracy and processing time are crucial factors to consider. Some studies have reported on the computational time and cost of using particular fusion methods, while others have developed more time- and cost-effective algorithms. Overall, evaluating the efficacy of MRI and CT image fusion is a challenging and ongoing area of research. Further development and validation are necessary before the technology can

be implemented in clinical practice. Nevertheless, initial findings have been promising, indicating improved image quality and additional diagnostic information.

6 Conclusion

Medical imaging is widely used for diagnosis and therapy purposes, as it provides crucial information for accurate diagnosis and treatment. However, the merged images obtained through image fusion do not always result in improved accuracy. Therefore, in this study, we propose a novel approach based on the dual-tree complex wavelet transform (DTCWT) for enhancing medical image fusion. Our proposed method leverages the improved shift variance and appropriate directionality detection of the DTCWT to generate a more accurate multi-modal fused image. Specifically, we use the DTCWT to decompose the raw images obtained from CT and MRI scans, extract the coefficients, and approximate them. The segmented fused image is then obtained by applying the inverse dual tree complex wavelet transform. The resulting fused image shows more precise information regarding the tumor boundaries, tissues, spectral, contour, and spatial features. Overall, our proposed technique provides an effective solution for enhancing medical image fusion.

7 References

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