DETECTION OF CEREBROVASCULAR DISEASES EMPLOYING NOVEL FUSION TECHNIQUE

Project report submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

By

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DECLARATION

We hereby declare that the work reported in the B.Tech Project Report entitled **"Detection Of Cerebrovascular Diseases Employing Novel Fusion Technique"** submitted at **Jaypee University of Information Technology, Waknaghat, India** is an authentic record of our work carried out under the supervision of Dr.Shruti Jain**.** We have not submitted this work elsewhere for any other degree or diploma.

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This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

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LIST OF ACRONYMS AND ABBREVIATIONS

Abbreviation	Meaning
AC	Alternating current(terms)
BRISQUE	Blind/Reference-less Image Spatial Quality Evaluator
CT	Computed Tomography
CS	Contrast Stretching
CLAHE	Contrast limited adaptive histogram equalization
CWCT	Cosine-Wavelet Component Transform
DC	Direct Current(terms)
DCT	Discrete Cosine Transform
DWT	Discrete Wave let Transformation
GLDS	Gray Level Difference Statistics
GLRLM	Gray Level Run Length Matrix
GLCM	Gray Level Co-occurrence Matrix
KNN	k-Nearest Neighbors
MR	Magnetic Resonant(Image)
PET	Positron Emission Tomography
PCA	Principal Component Analysis
PSNR	Peak Signal to Noise Ratio
RGB	Red, Green and Blue
RMSE	Root Mean Square Error
SNR	Signal to Noise Ratio
SPECT	Short Photon Emission Computer Tomography

SR	Spatial Resolution
SSIM	Structural similarity index measure
SVM	Support Vector Machine
WT	Wavelet Transform
2-D	Two Dimensional
F	Fused Image
R1	Reference image 1
R2	Reference image 2

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ABSTRACT

Advancement of technology has initiated support of high-tech computers in the medical sector which occasionally relies on image fusion methods. Detecting and diagnosing a disease with just one anatomical image can be time-consuming and challenging for doctors in the healthcare field. As a result, for a more detailed analysis, there is a demand of proposing a model which not only improvises medical images of the patient but also aid in localizing diseases and tumors in order to yield a better comprehension of the issue in question. This leads to superior diagnosis and therapies. Exploration of the field of image fusion also paves the way for further changes, which can be considered one of the reasons for interest. The emergence of non-invasive methods for tumor diagnosis and treatment is of significant importance due to medical advances. CT, MR, and PET images are common image modalities in the medical field.

The aim of this research is to implement various fusion algorithms based on traditional and proposed hybrid techniques. Techniques for machine learning Based on performance metrics, it has been discovered that the novel approach, Cosine-Wavelet Component Transform, outperforms conventional techniques. The various attributes were derived from the fused images, which were categorized using various machine learning techniques. Using a combination of both feature GLDS and shape, the Cosine-Wavelet Component Transform for SVM and kNN (k = 4) achieves a maximum accuracy of 98 percent and 92 percent, respectively. If there are a number of points in low dimensional space, KNN is a good choice; if there are fewer points in high dimensional space, SVM is a better choice.

Keywords: Multi-modal image fusion, enhancement methods, identification, attributes, performance metrics.

CHAPTER 1

INTRODUCTION

Over the last ten years, medical imaging has made significant progress. The need to increase diagnostic yield and achieve fast turnaround through robust knowledge processing has fueled technological improvements, which should lead to more effectiveness. It is becoming one of the most important aspects of everyday health applications including disease diagnosis and treatment. The development of automated systems for medical image processing that can effectively serve as an agent to help medical diagnosis has been a goal for many researchers. The quality of medical images is often unsatisfactory due to technological constraints, compromising the accuracy of human perception and subsequent medical image analysis and so its improvement is necessitated. The rapid advancements in emerging technology have also paved the way for the growth of high-tech medical imaging equipment.

As we know a device's computing capacity is incomparably greater whereas the human brain has a powerful skill in recognition and interpretation tasks that no analytical machine can match. On that account, medical imaging has become increasingly reliant on data obtained from multiple imaging modalities. This is due to the fact that the additional information obtained after image fusion increases the diagnostic efficiency. The image fusion may, for example, be between data from various modalities [1]. A variety of approaches can be used to divide the analysis of medical imaging into smaller parts such as, registration, enhancement, examination, and visualization of images. Image registration is perhaps the most important aspect of image fusion as it maps points of one imagery into the corresponding points of other imagery.While image enhancement produces better quality of the data to be analyzed.

Implementation of these techniques are critical for improving the information in images and making image datasets easier to comprehend in the clinical diagnosis process which may lead to desired outcomes, such that less time will be spent by specialists, a reduction in intra- and inter-observer gaps, and the provision of second opinions to non-experts. Feature extraction, classification, pattern recognition, statistical measurements, texture analysis, and a range of other approaches allow for more precise outcome interpretations, which could be critical for the research experiments' conclusions. Nonetheless, the dissertation discussed in this study focuses on fusion and enhancement of medical anatomies, followed by feature extraction and classification.

1.1 Image

An image is a two dimensional matrix .It is made up of two real variables, such as I (x, y), which represents the image's amplitude at the concerned coordinate point (x, y).**Fig 1.1** represents an image in matrix form with pixel values[2]. A pixel (also known as a picture element) is the smallest unit of data in a picture. Each one of the pixels that make up an image stored in computer has a pixel value that defines how vivid or what colour it should be. The pixel value in a grayscale image is a single number that reflects the pixel's brightness. Modern digital technology has demonstrated the ability to process multi-dimensional signals with a variety of devices ranging from digital circuits to sophisticated parallel computers.

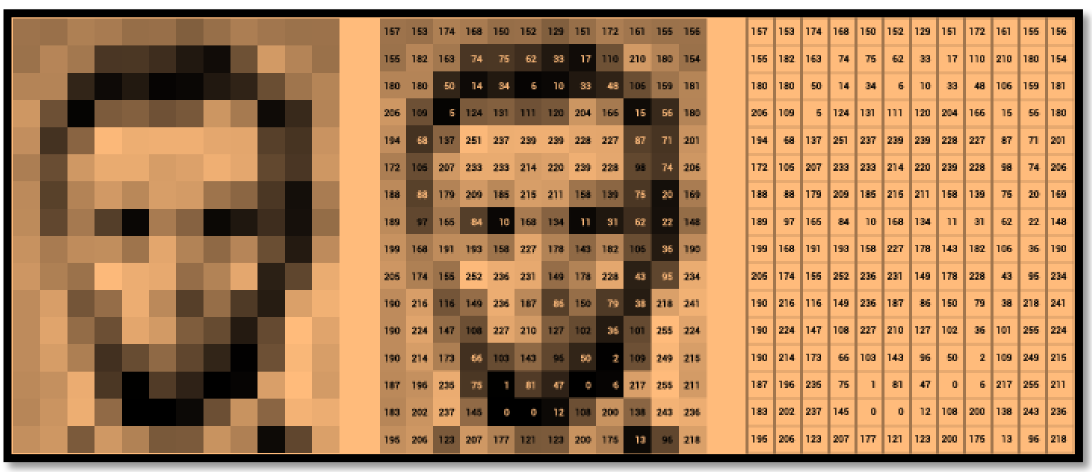


Fig.1.1: A visual representing an image in matrix form [2].

The most common requirement for image processing of photographs is that they be available in digitized form, that is, as arrays of finite length binary words. The provided imagery is sampled on a separate grid for conversion, and each sample constituent is measured for employing a finite range of bits. A computer system then processes the digitized image. A digital image is generated by converting an analogue signal to a digital signal. The conversion process involves sampling the image and dividing the sampled values. Processing takes place when the image is converted to bit data [3]. Image smoothening, image reconstruction, and image compression are all part of this technique. There are different types of digital image consisting multispectral, gray scale, binary and true color scales.

i. **True Color Image*:*** The color of each pixel in a true color image, also known as an RGB image, is determined by the combination of red, green, and blue intensities contained in each color plane at the pixel's position. A color map is not used in true color pictures. The dim level data in each phantom band is the real data stored in the advanced picture information. They are stored as 24-bit images in graphics file formats, with the red, green, and blue components each being 8 bits. **Fig 1.2** depicts a true color image [4].

Fig.1.2: A true color image [4].

ii. **Binary Images*:*** Binary images are the simplest type of image, and they can have two values, usually high contrast, or 0 and 1.**Fig 1.3** depicts a binary image. These images are often used in applications where the primary data needed is a general shape or blueprint, such as model optical character recognition. The characteristics function of an object in images can mathematically be represented as below:

$$b(x,y)\begin{cases} = 1 \; for\ points\ on\ the\ object \\ = 0 \; for\ the\ background\ points \end{cases}$$

Fig.1.3: Representation of binary image.

iii. **Gray Scale Image*:*** One-shading photographs are grayscale photographs with just one shade. They have dark level data in them. The number of bits used to represent each pixel determines the number of different dim levels that are available. The image contains 8 bits per pixel information, allowing us to have 256 different dim levels. Images of 12 or 16 bits per pixel are used in applications such as restorative imaging and space science. When a small portion of the image is rendered much larger to observe subtleties, these additional dim levels become useful. **Fig 1.4** displays a gray scale image.

Fig.1.4: Representation of a gray scale image.

iv. **Color Spaces (The RGB Color Space):** The RGB color space is the most widely used colour space. Each pixel's three bytes of data can be divided into three parts: one byte for the amount of red, another for the amount of green, and the third for the amount of blue.

The primary colours of red, green, and blue can be combined in various proportions to create any colour. There are 256 different shades of red, green, and blue available (one byte can accumulate a value from 0-255). Representation of an image getting divided into red, green and blue channels in **Fig.1.5.**

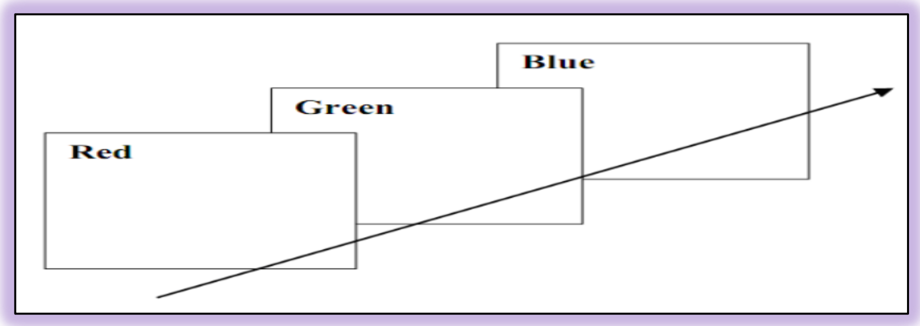


Fig.1.5: Representation of an image getting divided into red, green and blue channels [3].

v. ***Multispectral Image*****:** Multispectral images usually referred as bands, include information outside of the normal range of human sensory activity. This may include information from infrared, ultraviolet, X-ray, acoustic, or measurement systems. As a consequence of the information drawn not being directly accessible by the human system, these do not seem to be pictures in the traditional sense. However, information is typically represented visually by mapping various spectral bands to RGB components, such as Thematic Clerk and Multi Spectral Scanner images. By processing each band separately, all of the traditional single-band image processing operators can be applied to multi-spectral images. But processing of such images consumes more computational time and memory.

1.1.1 Medical Images

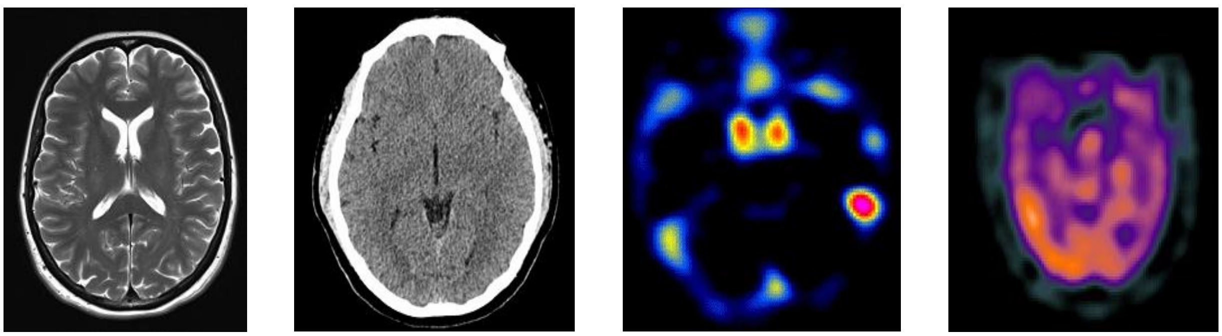
A medical picture, in most cases, contains both useful and useless information. The term "noise" refers to extraneous data that can be removed without degrading the picture. By removing noise information, a variety of denoising algorithms may recreate the original medical picture. The brain, for example, is a highly organized and delicate organ with intricate, curve-like configurations [5]. To correctly interpret the information in functional data images, radiologists must know the location of activations leading to brain disease. Brain defects include infections, bleeding, haemorrhage, seizures, and cancer, to name a few. The different modalities can be categorized as: (i) Anatomical image, which includes Computer Tomography (CT), Magnetic Resonance Imaging (MRI), X-ray, and Ultrasound (US), among others; and (ii) Functional image, which includes Photon Emission Tomography (PET), Short Photon Emission Computer Tomography (SPECT) [6][7] **Fig.1.6** indicates the visual comparison among different modalities.

a. **Magnetic Resonance Image (MR)*:*** MRI is a technique that uses a magnetic field and radio wave energy pulses to produce images of the human body's inner organs. It is used to detect issues such as injuries, brain tumours, bleeding, and vessel diseases. The cross-sectional images of the body retrieved from MRI signals are enhanced by mathematical models and provide superior information on soft tissue or non-bony areas of the body, as well as additional distortion and high contrast resolution. MR imaging is preferable to CT scanning for children because it does not expose them to ionising radiation.

b. **Computer Tomography (CT)*:*** Its other name is CAT scanning (Computerized Axial Tomography). It combines many types of imaging known as cross-sectional imaging into a single plan that can be interpreted. The CT scan reveals anatomic details about internal organs that standard X-rays cannot reveal. The x-ray tube is rotated around the patient and multiple images from various angles are collected. These images are fed into a computer system, which analyses them before creating a new image. CT emits more radiation and has a lower resolution than an X-ray, but it contains more detail as compared to an X-ray. Tumors, head infarctions, and abdominal disorders can all be detected with a CT scan. Bone dense structures and implants will be perceived with less falseness by CT, but physiological changes will not be detected.

c. **Photon Emission Tomography (PET)*:*** PET is a nuclear medicine imaging technique. In general, intravenous injections are used to aid doctors in diagnosing and assessing medical conditions in a painless manner. By monitoring important body functions including sugar absorption, oxygen usage, and blood flow, a PET scan assists physicians in evaluating the functioning of healthy organs and tissues.

d. **Short Photon Emission Computer Tomography (SPECT)*:*** The flow of blood into the tissues and organs is described using SPECT, a form of nuclear imaging test. Before the SPECT scan, a radio-labeled chemical injection is administered into the human body, which releases gamma rays that can be identified by the scanner. The information emitted by the gamma rays is collected by the linked device, and two-dimensional cross-sections are converted. A SPECT scan is used to see how blood travels through the brain's arteries and veins. According to research, it could be more beneficial to brain damage than MRI or CT scanning since it detects decreased blood flow to the injured area.



(a) **(b)** **(c)** **(d)**

Fig.1.6: A visual comparison of (a)MR (b) CT (c) PET and (d) SPECT images [7].

1.1.2 Attributes of Medical Images

a) **Resolution:** The resolution of an image refers to the amount of information it contains. A higher resolution picture has more detail. Spatial resolution refers to how well lines in an image can be resolved. When it comes to soft copies, the physical image size is less significant than the resolution needed for accurate diagnosis [8]. The limiting spatial resolution for digitised images is often calculated in line pairs. The mathematical formula for spatial resolution(SR) is given in Eq.(1):

$$\mathrm{SR} = \frac{m}{2f} \tag{1}$$

Here f denotes the Field of View (FOV) dimension and m denotes the number of samples in the matrix. The word "image size" will be used to refer to the total number of pixels needed to display the image in both horizontal and vertical directions.

b) **Dynamic Range:** The number of bits used to fully display the range of grey scales in an image to the required precision is known as the dynamic range of the image. The dynamic range within a given intensity window, when combined with the mapping function, determines how many more bits from the original are needed to fully exploit the display hardware's capabilities. 12 bits are needed, but this is only required in some regions for the latter [8]. The mapping can be automatically selected using a linear mapping feature to fully exploit the full display range for a particular Region of Interest (ROI) identified by the user.

c) **Contrast and Sharpness:** Contrast is the presence of a feature or structure in a picture in comparison to its surroundings. It's the distinction between the shades of grey or the degree of luminance in a picture. Sharpness refers to how abruptly blackening shifts at the intersection of two pieces [8]. The standard 256 grey values (8 bit) output by some capture devices are commonly used. The most advanced capture systems can also be capable of capturing up to 65.536 grey values (16-bit). This provides exceptional consistency at the cost of a larger file size and additional storage. When the signal-to-noise ratio is poor due to unfavorable circumstances, a lot of information is lost.

d) **Features:** A function in computer vision and image processing is a piece of data that is essential for solving the computational task associated with a particular application. Specific structures in the image, such as points, edges, or objects, can be used as features. A general neighbourhood operation or feature detection added to the image may also result in features [8]. Other features include motion in image sequences, shapes identified by curves or borders between image regions, and properties of such an area. The feature definition is rather broad, and the features used in a computer vision system can vary greatly depending on the problem at hand.

1.2 Constraints of Imaging Devices

Owing to the intrinsic properties of an imaging device, the contrast and accuracy of medical images degrade, resulting in incorrect diagnosis. The resolution of the device, the time required to scan, patient's motion at the time of scans, and the radiation emitted are some of the factors that affect image quality [9].

Device Resolution: The resolution of each device differs. The image volume is a grid with a small spacing between nodes, which is not visible in the final image. When two points in the patient's body are excessively similar to each other, the measured amplitude is an average of the neighbouring values. Such issues are defined as partial volume effect as it degrades the quantitative value of brain images.

Scan Time: When lying in the scanner, a number of patients experience anxiety. The scanning process should be time limited to minimise this. Furthermore, medical devices are only profitable if they are used frequently; otherwise, they are costly. The use of a MRI device allows for uninterrupted scanning of many patients. The number of samples collected and the image quality are also limited by the time of an image acquisition.

Patients Movement and Artifacts: The movement of the patient causes a blurring effect in the resulting picture when the intensities are measured. The arms and neck are the most often moved parts of the body. The sharpness of a region of the patient's body in the picture is affected by any movement in that region. Metal artifacts, such as a brain clip, prostheses, or implants, may trigger an artifact in the scan. These objects appear in the picture as bright lines emanating from the metal object's position. Because of the concentration of line objects around the metal object, the area around the metal object is generally not visible in the picture.

Emission of Radiation: The scans' accuracy is limited by the maximum radiation doses. The acquisition time will increase the resolution of a scan. Long-term exposure to X-rays, on the other hand, may result in serious illnesses such as cancer. As a result, the scan acquisition time and image resolution are reduced to reduce the risk of cancer.

1.3 Image Processing Methods

Image preprocessing aims at improving image information by reducing unnecessary distortion and noise, as well as enhancing image features for further processing. This method has numerous advantages, including elasticity, adaptability, data storage, and communication. With new innovations, it became faster, cheaper, and easier such that multi dimensional images can be processed[10]. There is no increase in image content information; just a more defined version of data is generated. Finding patterns, detecting edges, removing noise, and calculating statistics for texture analysis or image quality are all examples of image processing tasks. It is a broad term that encompasses a variety of techniques given below:

- **Image Enhancement:** a framework for optimising image data in preparation for further processing or analysis.
- **Image Fusion:** to combine different modality images, it uses mathematically based algorithms.
- **Segmentation of Image:** separating areas and items of interest is an operation.
- **Noise Suppression:** this can be done using morphological filtering or machine learning.
- **Feature Extraction:** a form of dimensionality reduction in which a large number of pixels in an image are efficiently represented in such a way that the image's most interesting parts are effectively captured.
- **Study of the Region:** a process that furnishes factual analysis.

1.4 Image Enhancement

Image enhancement methods are used to overcome the constraints of image acquisition and transmission systems. Its operations include the removal of noise and blur, the improvement of contrast and the adjustment of luminance. Enhancement can be used to reestablish a medical anatomy that has deteriorated due to intrinsic properties of a medical device or to enhance specific features of an image. Its purpose varies as per the context of application, and the requirements for enhancement are frequently subjective or too intricate to be easily converted to useful objective measures. Furthermore, in any given application, an image enhancement algorithm that works well for one type of image may not work as well for another. Median filter, Gaussian Filter, Contrast Limited Adaptive Histogram Equalization, etc are some of the filters or methods used in removing noise, sharpening and reorganization of key features.

1.5 Overview of Image Fusion

The process of image fusion entails extracting a large amount of vital information from the input images in order to produce the desired output image. Medical image fusion is the process of merging two or more imageries to produce a fused image with minimal distortion and no loss of detail. To facilitate image analysis visualization, interpretation, and processing, the image must contain redundant and complementary information from the source images. An image of a specific medical modality cannot retrieve important information because of its own limitations and differences in geometry, scale, and time. For medical diagnosis, this is insufficient. With respect to the fusion definition, one or more medical modalities must be fused using image fusion algorithms.

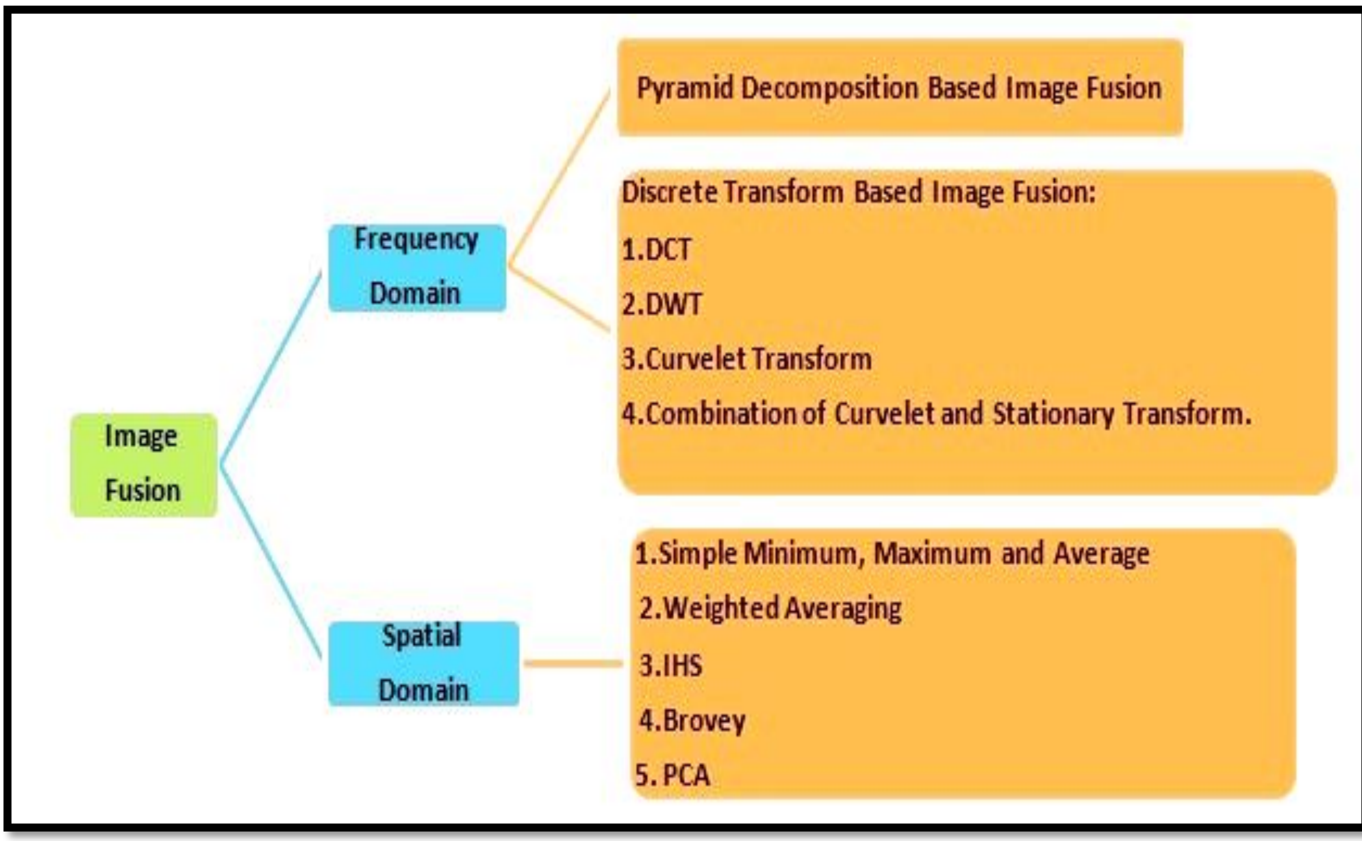


Fig.1.7: Types of image fusion methods.

Image fusion techniques can be performed at four different stages based on the levels of abstraction: signal level, pixel level, feature level, and decision leve l[11]. Signal-based level fusion combines signals from different sensors to create a new signal with a higher signal-to-noise ratio. Pixel-based method fuses images directly using pixels making it more suitable for medical diagnosis. In case of feature level fusion, various features of concerned areas are extracted so that they can be combined into one image. They are robust and more immune to noise. Decision level fusion methods are based on the results of original object detection and classification task. Generally, a preliminary decision from the feature based image fusion provides as the input to the decision level fusion. Spatial Domain and Frequency Domain image fusion techniques are two types of image fusion techniques. The above **Fig 1.7** shows the different types of fusion techniques.

The pixel level contrast reduction is led by the spatial domain oriented approach. Pixel values in an image are explicitly dealt with; pixel values are manipulated to produce desired effects. Fusion methods Simple Minimum, Maximum, and Average, Browey Technique Principal Component Analysis (PCA), and Intensity-Hue-Saturation (IHS) are categorized as spatial techniques. While in frequency domain the source imageries are mapped onto a localized basis, such that initial input image is first transformed into the frequency domain and then reconstructed. Some of the commonly used transform methods are Curvelet Transform, Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Non Sub-sampled Contourlet Transform (NSCT), etc. The steps involved to perform frequency domain based fusion are shown below in **Fig.1.8.**

Fig.1.8: The main steps in transform domain fusion technique.

1.6 Motivation

It is frequently observed that anatomical images are initially affected by artifacts. In order to enhance the image's accuracy, blur and noise in the image should be removed. The ultimate aim of image analysis in medical applications is to obtain not only qualitative but also quantitative data for objectively determining improvements in comparison to normal standards. Image processing methods such as enhancement and fusion algorithms help in drawing impartial conclusions in light of such issues. The massive amount of data produced however, needs to be transformed into an optimal collection of features by using the feature extraction method. Therefore, for improved human interpretations and subsequent learning, a more accurate and high quality image fusion technique is proposed and compared with traditional methods, while employing methodologies like enhancement and feature extraction of brain images.

1.7 Objective

The objectives of this study are as follows:

i. To develop and implement a novel, reliable approach for medical image fusion using Principal Component Analysis, Discrete Wavelet Transform and Discrete Cosine Transform in order to obtain better values of performance metrics.

ii. To compare various enhancement techniques such as Binarization, Median filter, Contrast Stretching (CS), and Contrast Limited Adaptive Histogram Equalization (CLAHE) on multi-modal images of the brain using fusion methods in order to provide improved image quality.

iii. To detect and classify Cerebrovascular diseases by employing feature extraction algorithms.

iv. To integrate the methods described above into a framework which would be beneficial for medical diagnosis and treatment.

1.8 Outline of the Report

The study encompasses multi-modal medical image fusion as well as enhancement methods in order to detect and classify medical disorders concerning the brain from its functional and anatomical images. The proposed framework aims at aiding medical diagnosis and treatment. The research is organized as follows:

Chapter 2 includes the analyses of research work by different scholars, providing a better understanding of techniques based on image processing.

Chapter 3 describes the process of multi-modal medical image fusion using conventional as well as proposed methods. The applications of few are examined in further chapters. Major emphasis is directed towards the determination of most efficient wavelet basis leading to better DWT performance.

Chapter 4 concerns with the implementation of enhancement techniques on anatomical images. On the basis of few performance metrics, enhancement method with better experimental and subjective values is chosen for further fusion process using PCA, DWT and PCA-DWT.

Chapter 5 illustrates the framework of proposed model for the identification and classification of Cerebrovascular diseases. The efficacy of proposed fusion methods are compared to that of traditional methods on the basis of qualitative measures. It includes the utilization of feature extraction and machine learning algorithms.

Chapter 6 provides the conclusion on the findings of this dissertation and proposed improvements, as well as potential study directions for further research.

CHAPTER 2

LITERATURE REVIEW

Many works were made in the field of multimodality image fusion among the published works, the followings were chosen as selective material, because of their closeness to the area of our research work:

- Image Fusion
  i. The authors of [12] investigated the efficacy of three separate image fusion approaches using various performance metrics. Emphasis of this study focused on the use of Pixel Level Fusion. Based on the findings, it was determined that PCA took the least amount of time to execute results as compared to block based fusion (BBF) and DWT. The findings were more accurate than those obtained using the block-based fusion process. This analysis lacked a visual representation of the data collection.
  ii. Medical image fusion was described by the authors in [13] as an ideation to refine visual content obtained by fusing CT and MR images, which can be useful for medical diagnosis. The 2D-DWT algorithm is implemented in a novel way, resulting in higher-quality fused images.
  iii. In [14], proposes a new DCT-based image fusion algorithm. It is extremely effective at preserving tissue material, texture, and edges in multimodal medical images. Furthermore, the algorithm is capable of producing high-quality fused images in less time.
  iv. In [15] a pixel-dependent image fusion technique based on differential evolution – discrete wavelet transform (DE-DWT) is proposed ,using substantial image fusion methods. In the simulations, CT and MRI images were used. Performance indices such as entropy, MSE, PSNR, contrast, and homogeneity indicate the effectiveness of the proposed DE-DWT process.

- Image enhancement
    - **i.** In [16], the authors address various possible strategies for improving the accuracy of underwater photographs. For improved picture quality, a hybrid approach combining DCP and CLAHE methodologies is provided. The DCP has been discovered to dim the picture, resulting in a low contrast image. So, in order to increase the scene's contrast, it was fed into CLAHE, and a strong contrast picture resulted. The image was eventually subjected to a colour correlation procedure, which improved the image's visual appeal.
    - **ii.** In the research [17], various filtering and contrast enhancement methods enhance low contrast, nose, and distorted images. For de-noising images, the median filter was less effective than the wiener filter, and CLAHE is excellent for increasing image contrast. These methods allow physicians and radiologists to make accurate diagnoses.
    - **iii.** The authors of [18] proposed an algorithm that uses Thresholding and Binarization techniques to improve fingerprint images. The algorithm begins by strengthening the thresholding mechanism, which is then followed by binarization. The images were less noise sensitive due to the faster image enhancement compared to the existing algorithms, according to the algorithm's experimental findings.
    - **iv.** On 150 images of malaria, authors of [19] used four types of contrast stretching methods: modified global, global, linear, and modified linear CS methods. Based on both quantitative and qualitative metrics, the proposed algorithms MGCS and MLCS proved to be more useful for improving image contrast than the standard GCS and LCS.

- Feature Extraction
    - **i.** The proposed method in [20] uses wavelet-based image fusion to produce a high-quality merged image with spatial and spectral detail. ANN is also used to identify brain tumors and assess their position and area in the process.
    - **ii.** In [21] the aim is to enhance the precision of the function extraction technique by focusing on anomalies such as brain haemorrhage and brain tumour. The brain

image extraction and brain image transformation process involves the incorporation of patient's MRI or CT Dicom image slices into a single image, noise reduction using three different methods, noise selection based on Peak Signal to Noise Ratio (PSNR) and Mean Squared Error (MSE) error metrics, skull elimination, and image enhancement.

iii. Authors of [22] introduce a hybrid technique for brain tumor prediction that combines support vector machine and modified fuzzy c-means. After noise reduction using Median Filtering in order to detect the affected region in MR image, modified fuzzy c-means clustering is used for image segmentation. Texture-based features, such as GLCM (Gray Level Co-occurrence Matrix) features, are used to extract features from the brain image. Thus, yielding more accurate and efficient results.

CHAPTER 3

A NOVEL MULTI-MODAL MEDICAL IMAGE FUSION

The fusion of multi-modality images involves the integration of more than two images so as to create a fused image with minimal distortion and no information loss. Anatomical images often contain redundant and complementary information which obligates the improvement in visualization, interpretation, and processing of images. Since medical image fusion provides additional information and storage for a single image rather than multiple images, storage costs are minimized effectively.

As a result, the image fusion technique will gain complementary knowledge used in biomedical research and treatment of clinical diagnosis for doctors by automatically merging different modality of medical images. There are various image modalities available in the medical field, which can be divided into two categories: anatomic and functional medical modality pictures. Anatomic or structural images, such as CT and MRI, provide high-resolution images of bone and soft tissue, while functional images, such as SPECT and PET, provide low-resolution images of blood vessel information flow.

3.1 Procedure of Image Fusion

The four fundamental steps carried out to perform image fusion are mentioned in **Fig.3.1** as below:

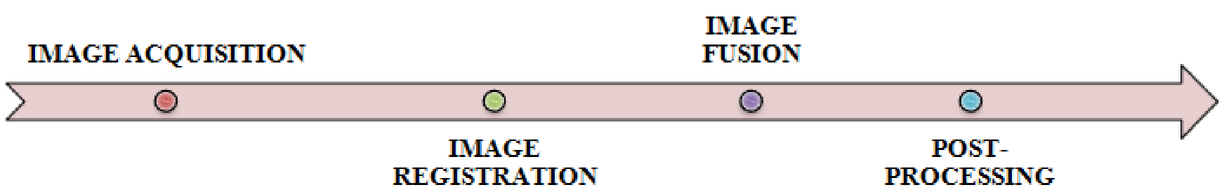


Fig.3.1: Image fusion basic steps.

3.1.1 Image Acquisition

In recent years, the demand for advanced digital techniques and lower equipment costs has increased in the medical sector. By using high-sensitivity acquisition systems with infrared radiation, images of human body are captured and processed. The approach falls under the category of non-invasive integrated technology, which examines the human body in both the X and Y directions. Automated digital image processing techniques and pattern recognition techniques are preferred for clinical assessment of thermal images. Images contain noise, which can cause a pixel's intensity to change, making classification difficult. Local computer networks that enable image recording, archival, and retrieval devices are referred to as Picture Archival and Communication Systems [23].Rather than point-to-point systems, teleradiology systems are likely to be connected to such networks in the future.

3.1.2 Image Registration

The procedure of image registration involves alignment of the sequence of source images in the desired order to overlap the corresponding features and details appropriately. The procedure operates in a way such that its resolution pixels of the images are mapped on to alike features in the resultant fused image. It involves different steps which are defined briefly in **Fig.3.2.**

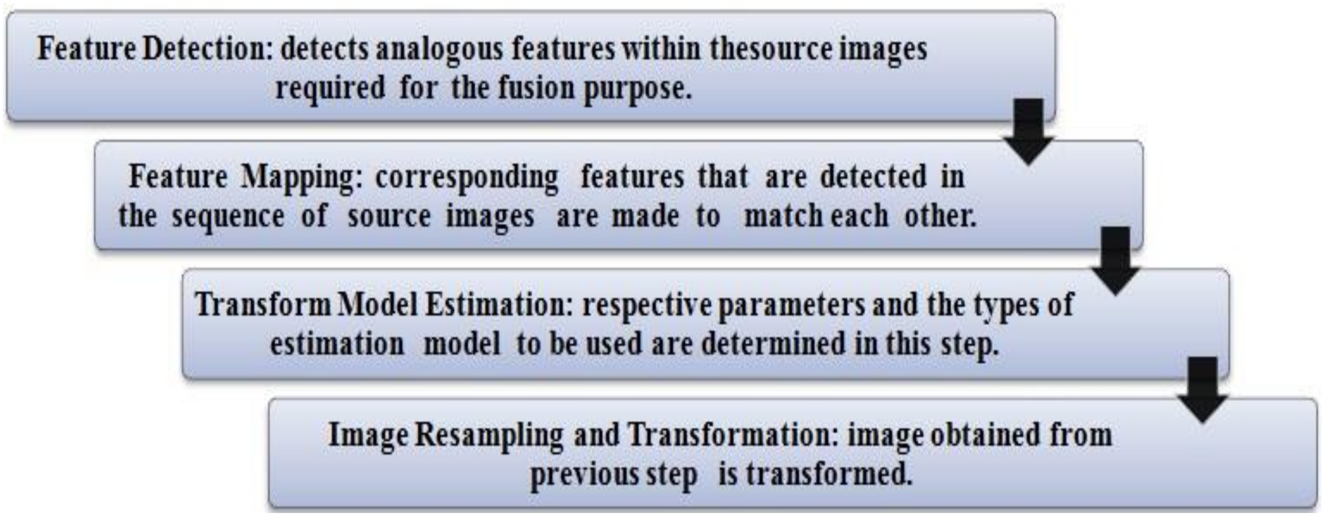


Fig.3.2: Steps involved in image registration.

3.1.3 Medical Fusion Techniques

The mechanism of the algorithms based on medical fusion is divided into three major steps: decomposition, fusion, and reconstruction. In decomposition, partitioning of a given level in order to obtain sub images at each level takes place. These sub images further get bifurcated into two categories: high frequency and low frequency sub-bands. The low frequency sub-band contains image approximation details. High frequency sub-band, on the other hand, contains image detail information. The goal of image fusion is to combine these low and high frequency sub-bands at each level using a specific fusion rule. The process of inversing the composite fused coefficients to obtain the desired output (fused) image are known as reconstruction. As a result, there are numerous multi-modal image fusion techniques in the literary works.

a) **Principal Component Analysis (PCA):** It is one of the most straightforward methods for constructing a fused image from many input images, in which fusion is performed as a weighted superposition of all input images [24]. The algorithm used in this analysis is shown in **Fig.3.3.**

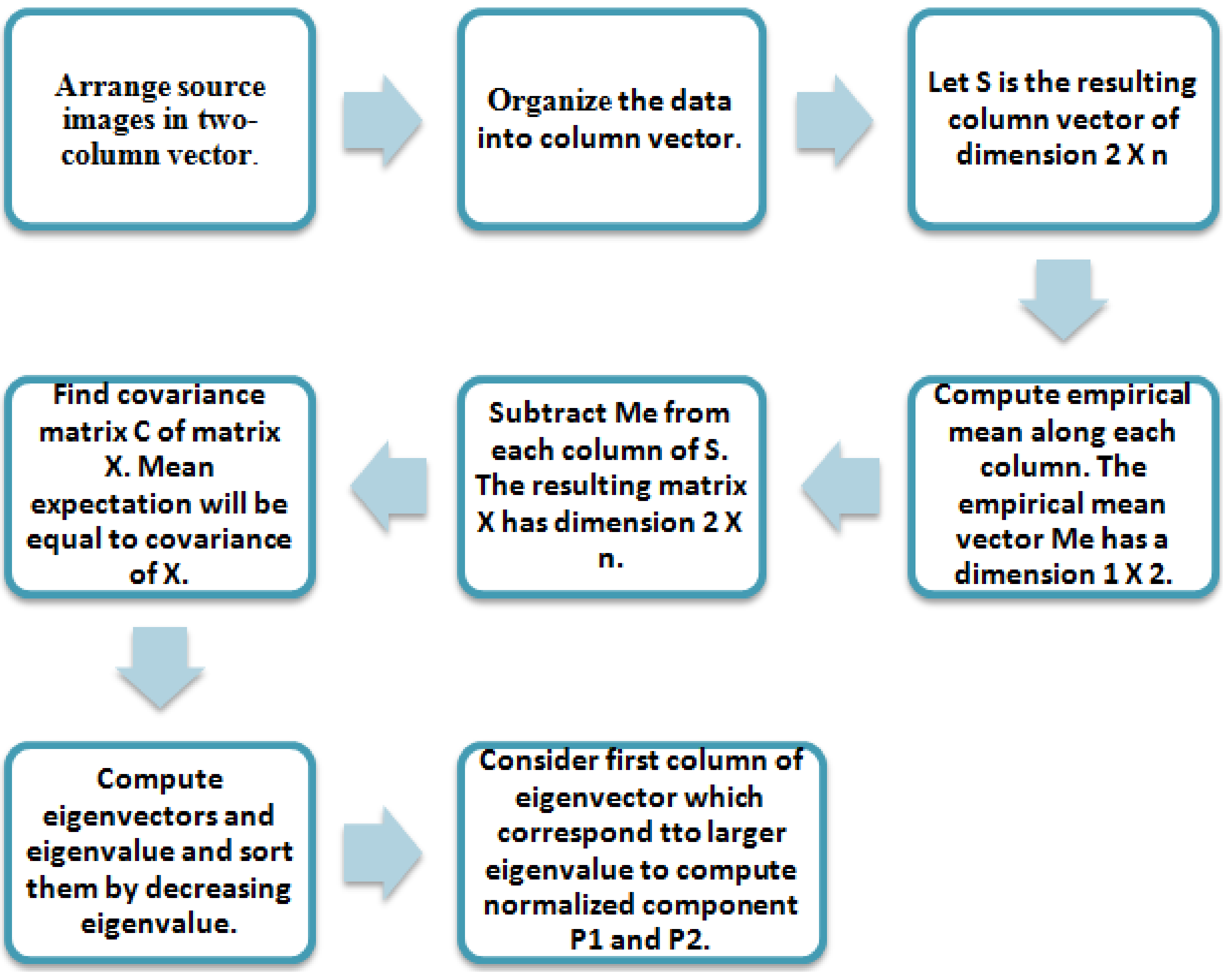


Fig.3.3: Implementation of PCA algorithm.

It employs transformations based on an orthogonal factor to produce a set of linear values obtained by transforming a set of opinions from conceivably related variables.

The principal components are the linear values that have been obtained. This transform is commonly used for image compression removal, random noise signal removal, and image rotation removal. The proportion of these principal components must be equal to and less than the parameters that are initial to the images.

By converting correlated variables to uncorrelated variables, it is possible to reduce the number of data sets with multiple variables while preserving the variance in the data set. It operates in a small space, which increases its performance. Its main advantages include being less susceptible to noise, reducing over-fitting, and improving data visualization. The image from transform would be a better approximation than the original image since the PCA transform image is imposed. Its aim is to expose the internal structure of data in an unbiased manner, used majorly for exploratory data analysis and development of predictive models.

b) **Discrete Cosine Transform (DCT):** The generation of an even symmetric periodic series in DCT eliminates the discontinuity as the symmetric signal passes smoothly from one cycle to the next. As a consequence, the DCT is free of leakage effects and Gibbs ripple. Furthermore, symmetric extension of the signal doubles its length, resulting in a factor of two improvements in frequency resolution [25]. It is also suitable for signal processing applications due to other properties such as energy compaction and the computational advantage of being real rather than complex. DCT fuses images using weighted coefficients and then recovers the fusion image using a recognition algorithm. In real-time applications, DCT-based image fusion is more appropriate and time-saving. As a result, we get clearer data.

c) **Discrete Wavelet Transform (DWT):** Data or signals in the real world often experience oscillations punctuated by transients. Fourier transform fails to effectively reflect the sudden changes in an image due to the fact that it produces data in the form of a sum of sin waves which are not localized in time or frequency and hence oscillate indefinitely. Smooth surfaces get disrupted by edges or sudden shifts in contrast in two-dimensional signals. Nonetheless, Wavelet Transform (WT) overcomes these limitations. A continuous signal cannot be used as the input for an image. As a result, in wavelet transform, the wavelets or input function are discretely sampled. To operate on an image's discrete pixel intensity values, this research uses Discrete Wavelet Transform.

The image is converted from the spatial domain to the frequency domain using 2-D DWT [26]. DWT employs a two-channel filter bank. The wavelet transform decomposes the image into low-low, low-high, high-low, and high-high frequency components by applying the 1-D DWT along the rows of the image first, and then along the columns to produce 2-D decomposition of the image, as shown in **Fig.3.4**. Approximation, horizontal, vertical, and diagonal coefficients are the names given to these four components. On obtaining the wavelet coefficients, appropriate fusion rules are applied. Finally, the inverse DWT is used to reconstruct the final fused image.

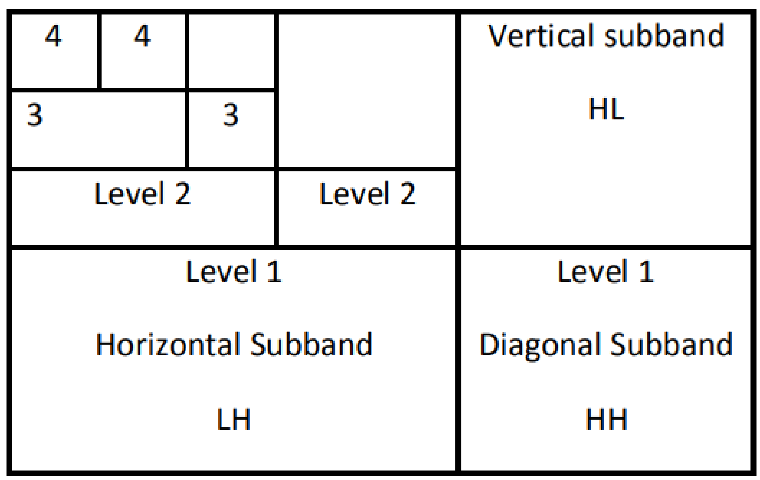


Fig.3.4: DWT decomposition of an image into corresponding sub-bands [26].

Biorthogonal, Coifflet, Daubechies, Haar wavelet, Symlet, Discrete Meyer, and reverse biorthogonal wavelet are some of the wavelet families. The pictorial representation of each type of signal are taken from [27] .The derivation from the mother wavelet is how the wavelet algorithm works. The mother wavelets differ in terms of support length, coefficient decay speed, symmetry and orthogonality, and biorthogonality of the resulting functions[28].

i. **Haar Wavelet:** It is discontinuous and resembles a step function. It represents the Daubechies 1 wavelet function. Haar decomposes the signal into two sub-signals of half the length . It has only one vanishing moment which makes it incompatible for restoration of smooth functions. However, being conceptually easy and rapid , it effortlessly detects the data which is time localized and is memory proficient.

ii. **Daubechies Wavelet:** The key feature of Daubechies wavelet is the availability of maximum number of vanishing moments for some predefined support length and denoted as dbN as shown in **Fig.3.5**.The name of the Daubechies is represented as dbN where N gives the order of the Daubechies wavelet. N usually varies from 1 to 8.

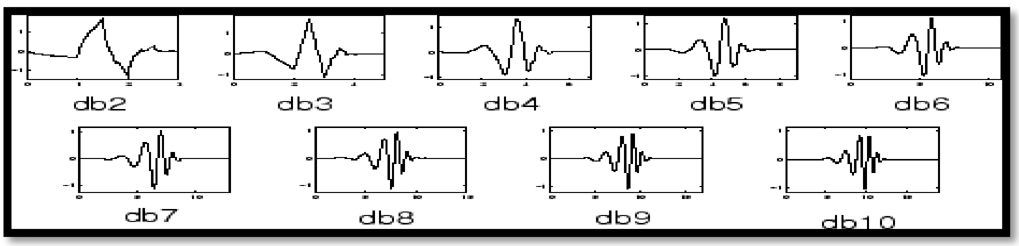


Fig.3.5: Daubechies represented as dbN where N gives order of the Daubechies wavelet [28].

iv. **Symlets Wavelet:** These are Daubechies least symmetric wavelets which are compactly supported and denoted as symN as shown in **Fig.3.6.**The construction of symlets is very similar to that of Daubechies but their symmetry is stronger than that of latter.

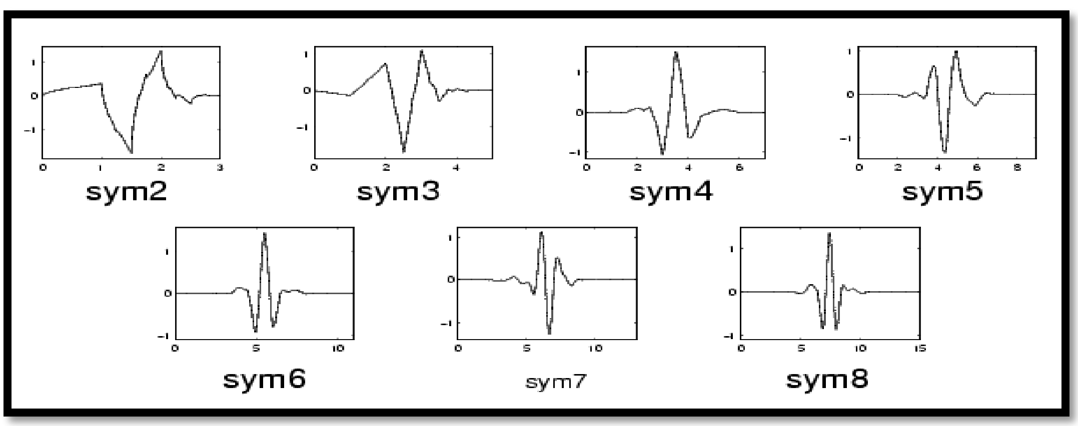


Fig.3.6: Symlets wavelets represented as symN [28]**.**

v. **Coifflets Wavelet :** these are more symmetrical than Daubechies mother wavelet and denoted as coifN as shown in **Fig.3.7.**

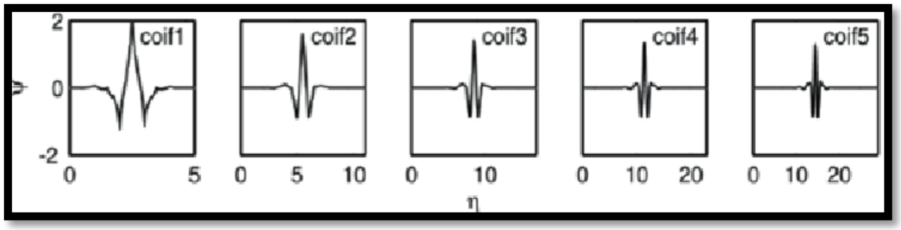


Fig.3.7: Coifflets wavelets represented as coifN [28]**.**

v. **Biorthogonal Wavelet:** It reflects the properties of linearity which is advantageous for image construction. They provide an additional degree of freedom than orthogonal wavelets denoted as biorN as shown in **Fig.3.8.**

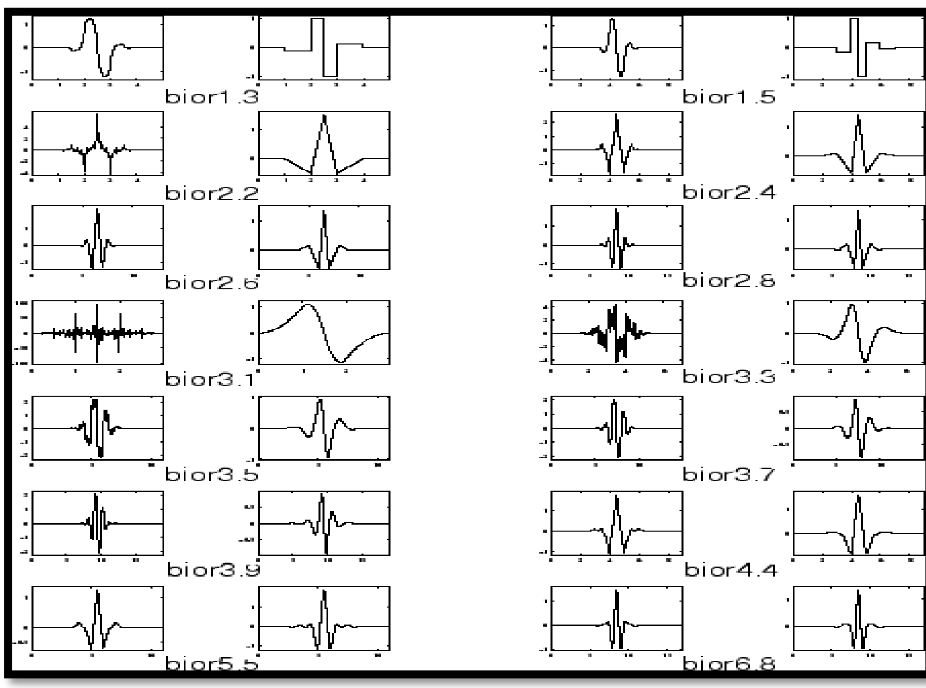


Fig.3.8: Biorthogonal wavelets represented as biorN [28].

3.1.4 Post Processing: Performance Metrics Evaluation

The output quality measurements used in this study allow for a quantitative comparison of different mother wavelet fusion schemes, with the primary goal of determining image clarity[30].

a. **Signal to Noise Ratio (SNR):** SNR is a performance metric used to evaluate the similarity between the reference image I_r and the fused image I_f.Here, M and N indicate the rows and columns values, respectively. It can be calculated using the Eq.(2). A higher SNR value indicates that both images are similar.

$$SNR = 10log_{10}\left\{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I_r(x,y)-I_f(x,y))^2}{\sum_{x=1}^{M}\sum_{y=1}^{N}I_r(x,y)}\right\} \quad (2)$$

b. Peak Signal to Noise Ratio (PSNR): When the reference image I_r and the fused image I_f are similar, the peak signal to noise ratio (PSNR) value will be high, and a higher value indicates better fusion. Here, M and N indicate the rows and columns values, respectively. It can be calculated using the Eq.(3).

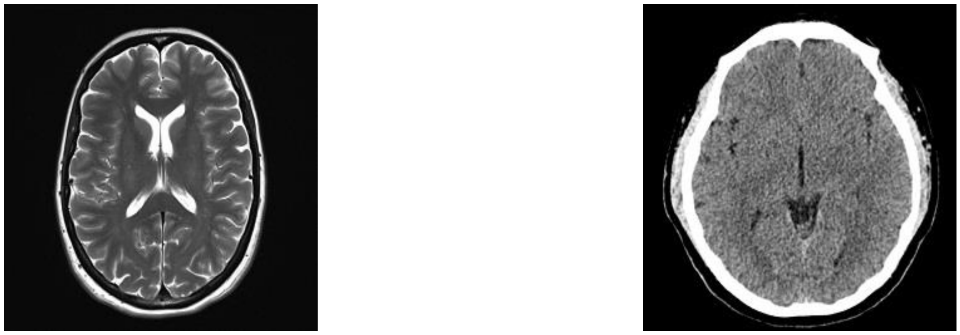
$$PSNR = 20log_{10}\left(\frac{L^2}{\sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(I_r(x,y)-I_f(x,y)\right)^2}}\right) \quad (3)$$

c. Root mean square error (RMSE) : The root mean square error (RMSE) corresponds to pixels in both the reference and fused images. If the reference and fused images are identical, the RMSE value is zero, and it increases as the dissimilarity between the reference and fused images increases. It is expressed mathematically by Eq.(4)

$$RMSE = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(I_r(x,y) - I_f(x,y))^2} \quad (4)$$

3.2 Analysis of Different Mother Wavelets

The aim of this section is to implement and determine which mother wavelet augments the fusion performance of the conventional DWT method. Also, the ambiguity related to which wavelet function should be used, for different applications, will be curbed. Different sets of CT-MR images [31] were analyzed but due to limitation of space only the set with better results are displayed in **Fig.3.9 (a)** MR image and **(b)** CT image of brain.



(a) **(b)**

Fig.3.9: Multimodal images to be analyzed; (a) MR image (b) CT image.

3.2.1 Methodology

In order to achieve a better understanding of the mechnism of discrete WT, nine variants of mother wavelets are considered. The procedural steps are briefly explained in **Fig.3.10**.

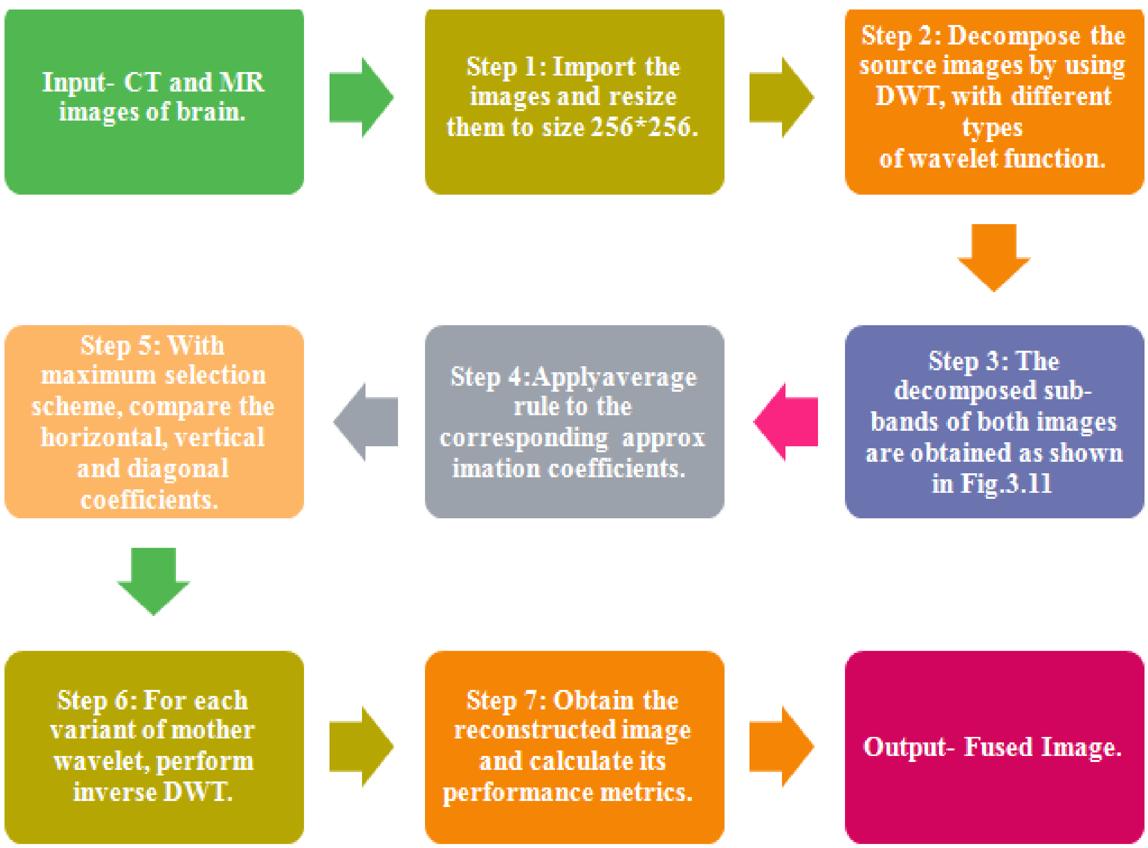


Fig.3.10: Flowchart of DWT image fusion using different mother wavelets.

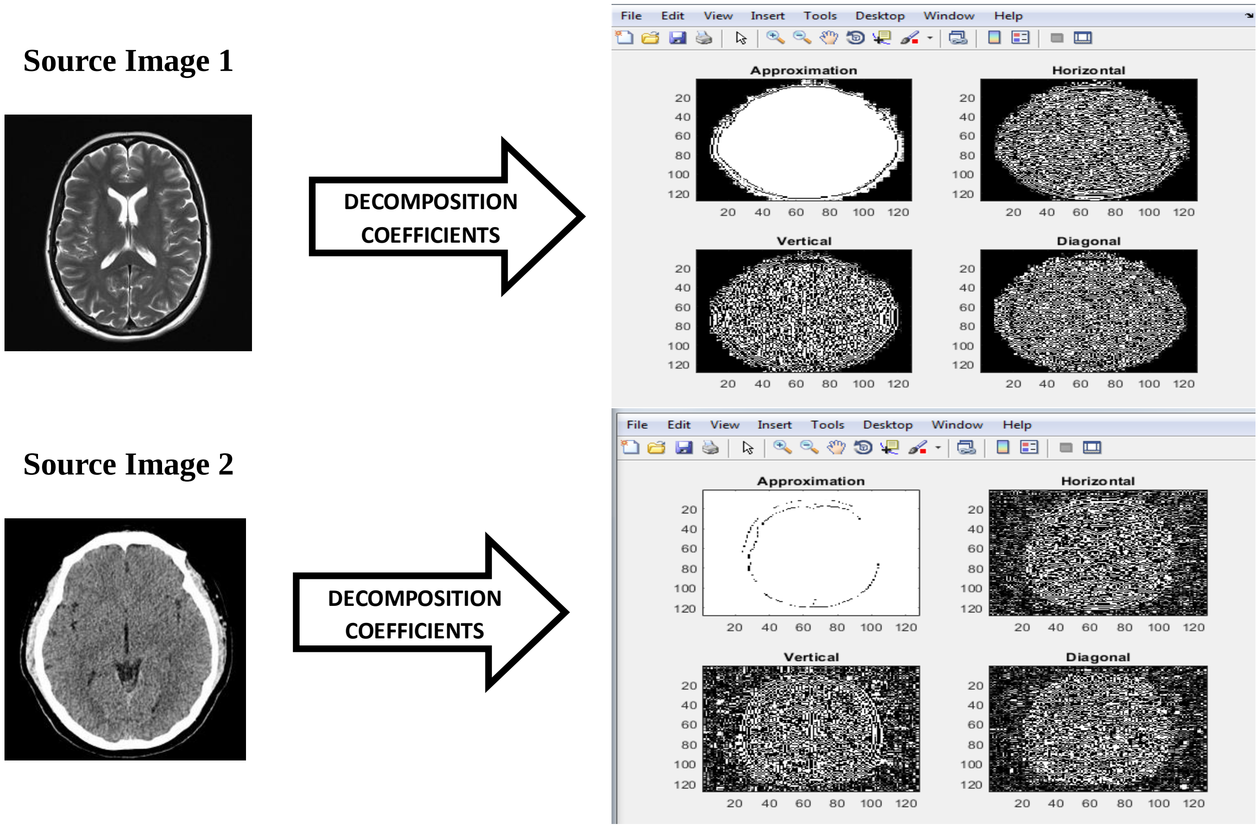
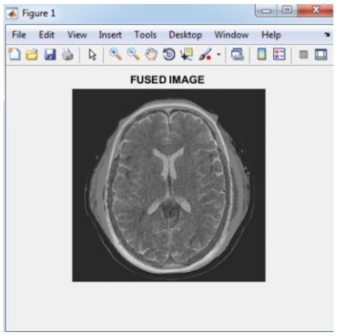


Fig.3.11: Decomposition of source images into their corresponding sub-bands, Approximation, Horizontal, Vertical and Diagonal.

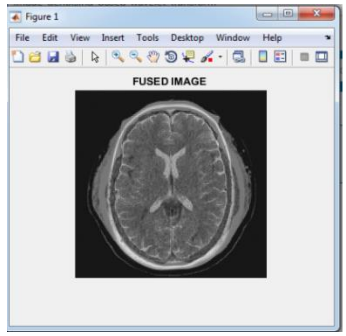
3.2.2 Discussion of Experimental Results

The relevant information from two or more source images is fused into one image which will be more detailed and informative than any of the other source images. DWT is implemented using nine variants of wavelet functions and experimental outcomes for each basis are showcased in **Fig.312.**

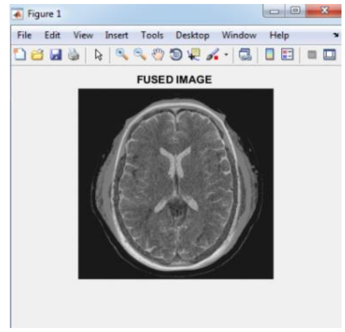
For a quantitative as well as qualitative comparison, performance metrics like RMSE, SNR, and PSNR are employed**.** Table 3.1 represents the PSNR, RMSE and SNR values between fused and source images.



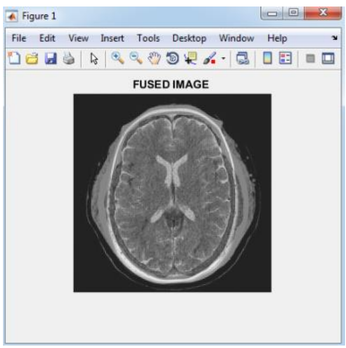
(a) db1



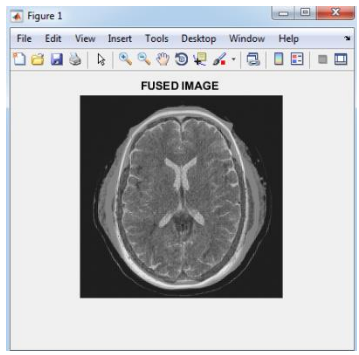
(b) db2



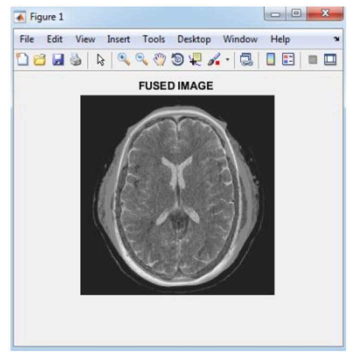
(c) db4



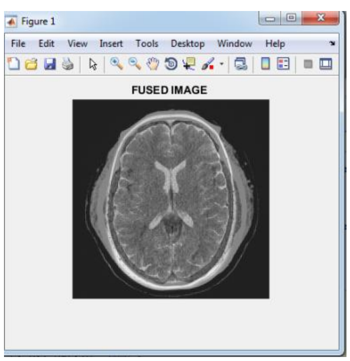
(d) coif2



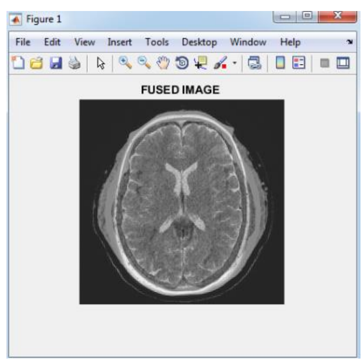
(e) coif4



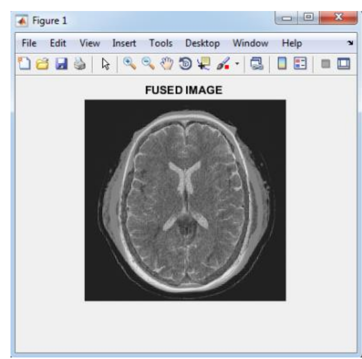
(f) sym4



(f) sym6



(g) bior2.2



(h) bior3.3

Fig.3.12: DWT fused images for different mother wavelet.

Table 3.1: Comparison on quantitative evaluation of wavelet basis for fusion performance.

Mother Wavelets	PSNR (between source image1 and fused image, dB)	PSNR (between source image 2 and fused image, dB)	RMSE (between source image1 and fused image, dB)	RMSE (between source image 2 and fused image, dB)	SNR (between source image1 and fused image, dB)	SNR (between source image1 and fused image, dB)
db1	15.41	15.41	9.74	9.52	13.87	13.94
db2	15.62	15.67	9.21	9.21	14.24	14.24
db4	15.49	15.45	9.12	9.94	13.98	13.75
coif2	15.48	15.45	9.08	9.91	13.56	13.77
coif4	15.46	15.44	9.00	9.87	13.67	13.55
sym4	15.48	15.45	9.08	9.92	13.45	13.71
sym6	15.47	15.44	9.02	9.89	13.64	13.57
bior2.2	15.46	15.43	8.95	8.81	13.66	13.66
bior3.3	15.48	15.41	9.07	9.75	13.87	13.92

From the above Fig.3.12 and Table 3.1, it is inferred that the Daubechies mother wavelet (db2) of discrete wavelet transformation technique provided better results for the fused image in terms of SNR, PSNR, and RMSE for the fused and reference image when compared to the others after evaluating the obtained experimental results and keeping in mind the values of considered qualitative steps.

3.3 Hybrid Fusion Techniques

Implementation of fusion techniques on anatomical images provide access to more medical information by combining the complementary and contrasting attributes of reference images into a single one. However, it is observed that traditional medical image fusion methods are incapable of producing high-resolution images. As a result, there is a compelling need to use hybrid fusion techniques to achieve the objective of improving the effectiveness of a fusion process. The application of each of the methods described below is discussed in later chapters.

a) **PCA - DWT***:* It is a technique that combines discrete wavelet transform and principal component analysis. It amalgamates the advantages offered by each process, resulting in fusion performance that outperforms their individual efficiency. Although discrete WT provides directional information in its decomposition stages, PCA produces less abrupt spectral features. As a result, more spectral and spatial information is preserved, and the fusion results obtained using this approach is more effective.

b) **PCA-DCT***:* A hybrid fusion technique developed by integrating two traditional approaches, DCT and PCA. Given that DCT generates broad quantized coefficients, some of which are localized in low frequencies, resulting in excellent energy compactness, and edges contribute to high-frequency coefficients, the algorithm integrated with PCA is focused on selecting the frequency band with the highest energy value. It was also discovered to be comparatively more time-saving. Data compression and pattern recognition are aided by PCA. The methodology proposed is briefly explained in Algorithm 1.

Algorithm 1: Methodology for fusion of anatomical images using PCA-DCT method.

Input : Source Image
Output : Fused Image

Step 1. Import input images of distinct modality from the database.
Step 2. Rescale the images to size 256*256 after converting them to gray color from RGB.
Step 3. Improve the visibility of vital details by processing both imageries using different enhancement algorithm.
Step 4. Level shifts the test images by 8 and then bifurcate them into 8*8.
Step 5. Extract the corresponding AC and DC coefficients of both DCT-wrapped images.
Step 6. Apply PCA to the AC coefficients and obtain the corresponding principal components.
Step 7. Display the resultant fused image.
Step 8. Evaluation of performance metrics.

---

c) **Cosine-Wavelet Component Transform (CWCT):** Because of the persistent localize peculiarity in both the time and frequency domains, discrete wavelet analysis has become one of the most widely used frequency domain fusion methods. However, in cases, when dealing with anatomical images of brain where valuable details are situated within its complex structure, wavelets might fail to perceive the image's line and plane singularities. The fused image gets affected by pseudo-gibbs phenomena leading to suppression of crucial information Therefore, to achieve more accurate results integration of algorithms is necessitated. In view of above, the study proposes a novel technique for multi-modal medical image fusion.

This methodology, briefly explained in Algorithm 2, utilizes the advantages of DCT and PCA along with enhancement methods to overcome the limitations of discrete WT. On decomposing the datasets using discrete wavelet transform, the corresponding frequency sub bands are fused using DCT as it provides good balance of information packing capacity and computational complexity. On obtaining the AC coefficients, apply PCA such that the details with high variances are sustained, removing those with little change. This reduces the computational time and only the components comprising majority of the original dataset will be reconstructed. DCT offers better frequency information but less spatial resolution. As a consequence, frequency details are more over the spatial ones. Nevertheless, the use of DWT will furnish the fused image with better spatial resolution

Algorithm 2: Methodology implemented for fusion anatomical images using CWCT technique.

Input : Source Image
Output : Resultant fused Image

Step 1. Import input images of distinct modality from the database.
Step 2. Rescale the images to size 256*256 after converting them to gray color from RGB.
Step 3. Improve the visibility of vital details by processing both imageries using different enhancement algorithm.
Step 4. Decompose the test images using DWT to produce the corresponding four frequency sub bands.
Step 5. Apply DCT wrapping and extract AC and DC attributes of each image.
Step 6. Convert AC coefficients to principal components by applying PCA.
Step 7. Reorganize key features with inverse DCT.
Step 8. Use inverse discrete WT to reconstruct the desired fused image.
Step 9. Evaluation of performance metrics.

3.4 Conclusion

Medical image fusion tools that are imported from outside India are used by highly regarded medical institutes, whether private or government medical colleges. As a result, these tools are becoming increasingly unaffordable for small clinics or hospitals, especially in rural areas. As a result, there is a critical need for low-cost indigenous tools in these areas to supplement the demand for this high-priced equipment. The majority of the algorithms in the literature are optimised for images that are nearly identical. As a result, different algorithms can be designed to work well with various image fusion methods. After evaluating, we can infer that visual characteristics should be used to determine the outcome of fusion. On the basis of performance metrics, the most appropriate mother wavelet was db2 (Daubechies mother wavelet) when nine separate mother wavelets (DWT) image fusion techniques were considered. Also the applications of proposed fusion algorithms will be implemented in chapters ahead.

CHAPTER 4

ANALYSIS OF FUSION TECHNIQUES ON ENHANCED MEDICAL IMAGES

In the previous chapter, a comparative analysis is conducted in order to determine usage of which mother wavelet escalates the performance of DWT fusion technique. However, the quality of fused images is observed to be distorted which can result in minute information or features being overlooked. Also, at times, owing to the intrinsic properties of an imaging device, the contrast and visibility of medical images degrade, resulting in incorrect diagnosis; therefore, the image quality must be improved prior to the fusion process. Feature extraction, and quantitative analysis are all hampered by noise, which obscures image information.

Practically it is not feasible to obliterate all of the noise components present in the image; nonetheless it is possible to reduce the noise to a level acceptable for diagnosis. So, once image enhancement is performed to improve image quality, it aids in subsequent image processing processes such as medical fusion, extraction of features, classification and suchlike. The aim of this chapter is to thus, utilize the benefits of spatial enhancement methods in order to obtain higher-quality images. Performance comparison of four commonly used enhancement techniques, namely Binarization, Median filter, Contrast Stretching (CS), and Contrast Limited Adaptive Histogram Equalization (CLAHE) is encompassed.

4.1 Enhancement Technique

Clinical image enhancement enhances the image perception of details for visualization purposes by increasing low contrast and minimising distortion in lower and higher frequency levels. Image enhancement is necessary for improving the appearance and the attributes contained in the image. Various types of noise could be observable during image conversion from one form to another, such as image acquisition, image copying from one location to another, digitization, and image transmission.

Apart from enhancement, image restoration is another image analysis technique in image processing that employs the principle of prior awareness of noise, degradation. It first models the degradation pattern, and then uses the inverse mechanism to reverse it. A degradation or distortion function may be used to reflect noise [32]. The formula must include various steps on which the image quality is to be improved by combining various methods of restorations, such as eliminating blurring caused by the deterioration function, then noise reduction using Weiner filter, wavelet, and blind convolution function dependent restoration. The image f(n, m) is a source input image, and the function f(n, m) is a function (restoration). Image restoration from deterioration (linear) Blind deconvolution, weiner, pseudo inverse, and inverse filters are among the filters used. Noise and motion blur, for example, are common types of deterioration that are represented by the spread feature. The basic steps are shown in **Fig 4.1.**

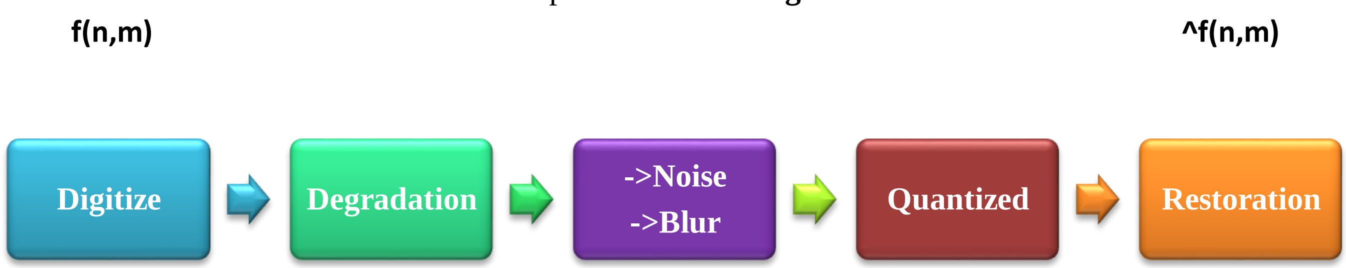


Fig.4.1: Representation of basic steps involved in image restoration.

In enhancement, degradation is rarely modeled. Restoration, on the other hand, aims to restore or fix an image that has been tainted by previous degradation. The image processing research is divided into two categories: image enhancement and image restoration. Both enhancement and restoration procedures aim to improve picture quality and are appropriate for either spatial or frequency domain [33]. The difference is that enhancement is, to a large extent, a subjective process, which means it is a heuristic technique for altering a picture to achieve the spectator's pleasing features. The technique of image restoration, on the other hand, necessitates the formulation of a criterion that will provide the best approximation of the desired result. **Fig.4.2** shows the different enhancement and restoration techniques. As a result, the image enhancement approach must be used to remove noise artifacts while preserving the image's original structure.

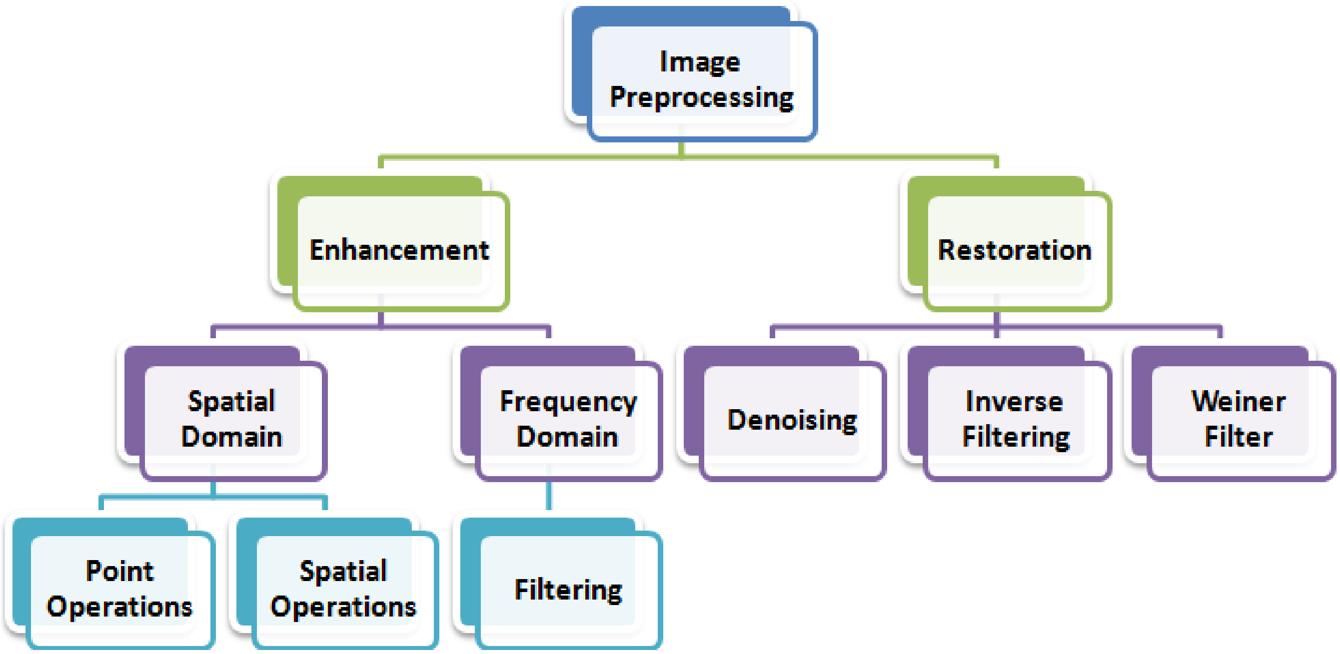


Fig .4.2: Types of Enhancement and Restoration image preprocessing techniques.

4.1.1 Types of Enhancement Techniques

The different enhancement techniques considered in this study are as follows:

i. **Binarization:** It is the method of transforming data variables (features) of any unit into binary vectors in order to improve the efficiency of classification algorithms. Binarization, for example, is the process of changing the gray-scale of a source picture from 0-255 to 0-1 spectrum units. It works by determining a certain threshold in the histogram, after which the histogram is divided into two parts, each depicting one of two objects[34]. Sometimes, data information necessitates the use of mean, median, and entropy, at other times, the data is represented by a histogram.

The Otsu method, developed by Nobuyuki Otsu in 1979, is a classic binarization technique. Since it chooses a threshold value that reduces the intra-class difference between black and white picture components, it's also known as the thresholding technique. It converts a grayscale image to a bi-level image. The pixels are divided into two groups by the Otsu method: background and foreground. This determines the best threshold value for separating the image into two groups. The threshold value is chosen with the aim of maximising between-class variance while minimising within-class variance.

Since degraded images do not usually reveal such a clear-cut pattern, the Otsu method gives better output limited to only those images that have clear bi-modal pattern when weighted within a class variance of two classes. It also has a hard time performing in pictures of poor lighting and shadow.

ii. **Median Filter:** This is a nonlinear sliding window smoothing technique that is often applied to digital images to reduce two forms of noise: pepper and salt. As shown in Eq.(5), the noisy value of the digital source image is swapped for the neighborhood's median value.

$$y[a,b]=\textit{median}(x[k,l] \quad (k,l) \ \varepsilon \ \omega \tag{5}$$

median(x[k,l] (k,l) represents the input matrix with corresponding pixels to be transformed by the filter, and y[a,b] represents the filter's centre value of manipulation. It is the fundamental building block upon which most advanced image filters are built [35]. Writing and speech recognition, radar, object segmentation, and sonar are only a few of the applications. Every image pixel is visited by the median filter, which overlays the centre value on it. The brightness values of each pixel inside the window are organized in a systematic manner, and the median brightness value in the filtered image replaces the window's centre value. Since sorting is a time-consuming operation, a Median Filter has a significant computational cost. The median value of the neighbourhood is substituted for the noisy value of the digital source image.

iii. **Contrast Stretching:** Only a limited portion of the potential spectrum of pixel intensities is used because we now know that many images have low contrast. The contrast of the results may be increased or stretched to correct this condition. Contrast stretching is a 'point procedure,' which means that each pixel in the input data corresponds directly to a pixel in the output image. Local Contrast Stretching Method and Global Contrast Stretching Method are two different kinds of Contrast Stretching.

Equalization of contrast across the image in the Local Contrast Stretching approach allows you to see image information in places that were previously very bright or very dark[36]. It increases the visualisation of structures in both the darkest and lightest sections of the picture by changing the intensity value of features locally. Where there are a small number of local pixels in an area, using the global approach is ineffective and produces undesirable results. As a result, the local method can be used to improve contrast in such images. The initial contrast determines the amount of stretching to be applied in the neighbourhood.

The value of global contrast in the Global Contrast Stretching method is an aggregate of local values for each small portion of the image in question. This approach can be used to classify algorithms used in global stretching and histogram equalisation. When images have a high global contrast value, they provide a lot of detail. When the contrast value is lower, the amount of detail present is considered to be lower, resulting in a more uniform appearance. This approach, on the other hand, will not work for images with a lot of variance in spatial properties[37]. The intensity distribution of the picture can be used to explain the variations between local and global differences.

At both ends of the illumination spectrum, typical global contrast enhancement will not achieve acceptable local contrast. Over dark areas, a global contrast stretch is more likely to saturate light areas, and vice versa. Since global contrast stretching has a limited dynamic range of variance, it is usually not used in image processing techniques. It is, however, useful when demonstrating the differences between local and global outcomes. The local contrast stretching algorithm was used in the contrast stretching experiments in this project.

iv. **CLAHE:** Histogram equalisation is a commonly used image enhancement technique that uses contrast limited adaptive histogram equalisation. The approach is straightforward, and the computational load is small. It's also suitable for coloured pictures. CLAHE is an extension of AHE, in which all pixels adjacent to all functions are transformed[38]. CLAHE limits or restricts the contrast, uses the full available value on the clip, and returns it to grey scale, while AHE does not. CLAHE, unlike other histogram equalisation methods that work on the entire image, works on a small portion or section of the image called tiles. Each tile is equalised separately, then adjoining tiles are combined with bilinear interpolation to eliminate the boundary edge and prevent the amplification of any noise in the picture. The basic algorithm for using the CLAHE technique to enhance individual image regions is shown in **Fig.4.3**.

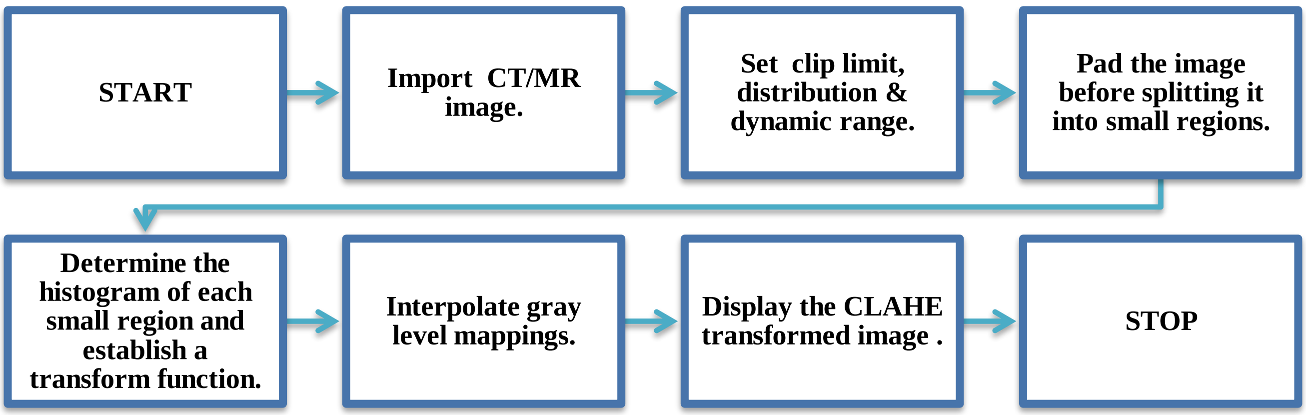


Fig 4.3: Flowchart of steps involved in CLAHE algorithm.

4.2 Methodology

The comparative evaluation of different enhancement algorithms using PCA, DWT and PCA-DWT is encompassed in this section. Four different pairs of images [39, 40, 41, 42] were considered. Until converting to grayscale, the source images were resized to 256 pixels by 256 pixels.

The intra-cerebral haemorrhage in the brain is visible in SET I. On the left side of the CT image, SET II depicts the presence of a small "residual hematoma," whereas the MR represents hematoma resolution and a minute parietal ischemic lesion. The MR portrays hematoma resolution as well as a minor parietal ischemic lesion. SET III reflects the findings of a 73-year-old man in whom the CT picture reveals a tumour with finger-like vasogenic edoema in the right frontal lobe, and the MR revealed a sub-acute lobar haemorrhage. The SET IV depicts a simple brain anatomy. **Fig.4.4** shows the CT-MR images that were considered.

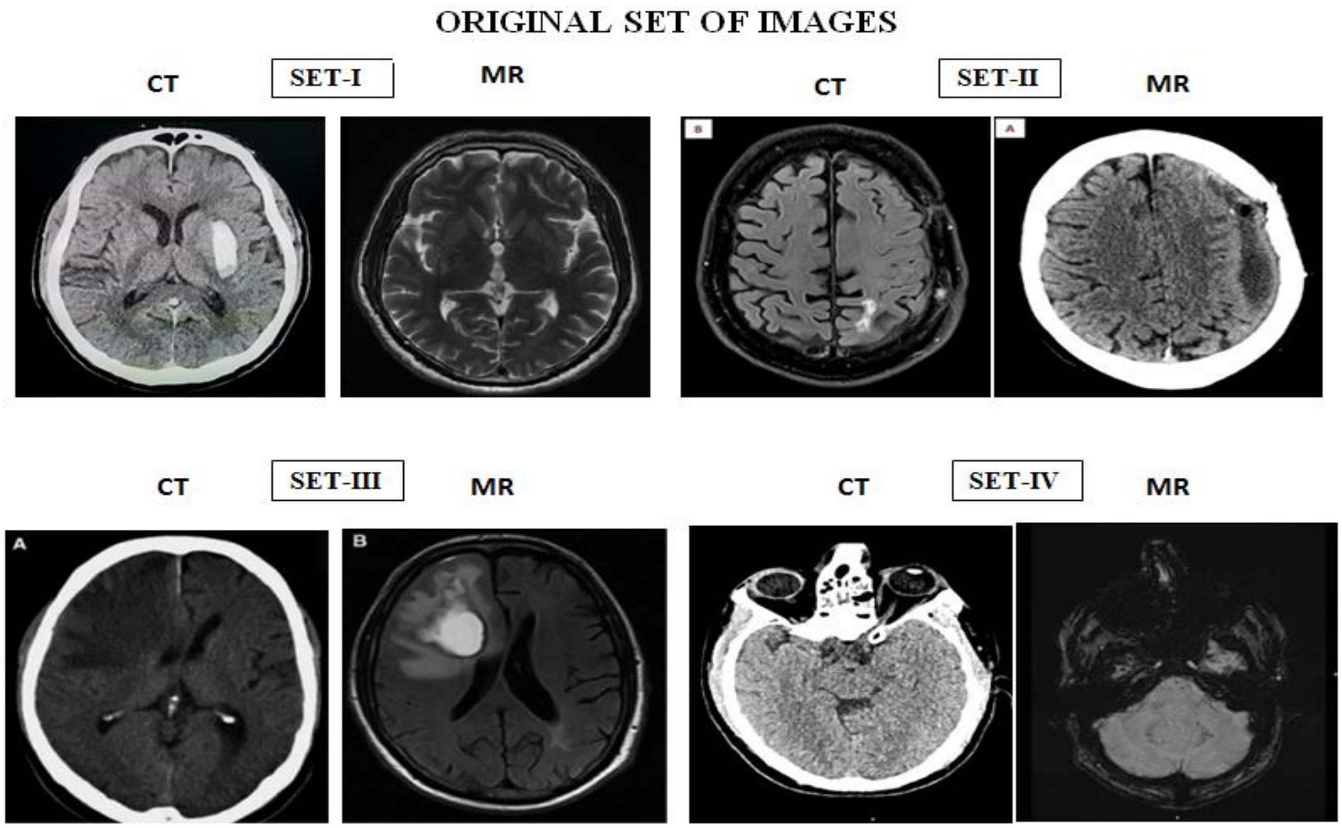


Fig.4.4: Original sets of CT-MR images considered for experimentation.

Each enhancement technique, such as Binarization, Median Filter, Contrast Stretching, and CLAHE, is applied to the data images after the image registration process.

Algorithm 3: Methodology for implementing each of the image enhancement methods.

Input : Original Image

Output : Enhanced Image

Step 1. Select the medical images ,followed by conversion to gray scale.

Step 2. Resize all images(CT-MR) to equal dimensions.

Step 3. Each image is processed by the enhancement algorithm applied(Binarization/Median Filter/Contrast Stretching, CLAHE).

Step 4. Resultant images are evaluated using *brisque*.

4.2.1Performance Metrics

Medical images must be examined for accuracy before being used in a variety of processes and applications. This allows medical practitioners to make impartial and correct diagnoses. The no-reference efficiency metric "brisque" is used in the first half of the experiment to determine the most effective enhancement technique. To assess the efficiency of the enhancement technique, the enhanced images are also processed using PCA, DWT and PCA-DWT..The quantitative analysis is performed with reference image approach. PSNR, SNR, and SSIM are the efficiency metrics used [32]. In general, a smaller brisque value means a better value. A higher SNR value, on the other hand, means that the reference and fused images are similar. A higher PSNR value means that the fusion technique is performing well.

a) **Structural similarity index measure (SSIM):** The pixel intensities of regional structures are compared between the reference and fused images. It can range between -1 and 1. The input and fused images are identical if the values are close to one. Its mathematical Eq. (6) is expressed as:

$$SSIM = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \tag{6}$$

b) **Blind/Reference-less Image Spatial Quality Evaluator (BRISQUE) :** This is a non-reference consistency metric that compares the picture in question to a standard model built from data from natural scenes with similar distortions. A higher perception of accuracy is shown by a lower ranking. It's a model built within a data set of related differential mean opinion score (DMOS) values, and it's based on "help vector regression" (SVR). The archive contains clean versions of distorted photographs, as well as evidence of recorded anomalies, compression artefacts, blurring, and noise. At least one of the distortions on which the model was trained should be present in the image to be scored.

4.3 Result and Discussions

The perceived outcomes for each of the enhancement strategies are shown in **Fig 4.5, 4.6 4.7, and 4.8**. The experimental findings are divided into two graphs: one for CT image analysis and another for MR image analysis, with the corresponding enhanced images.

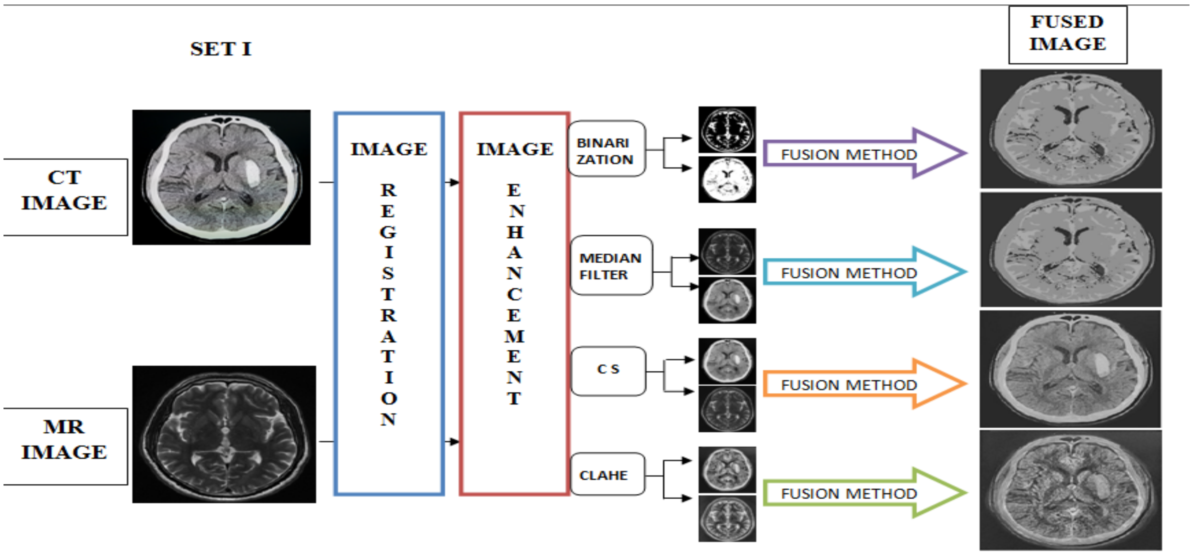


Fig.4.5: Resultant enhanced and fused images for SET I.

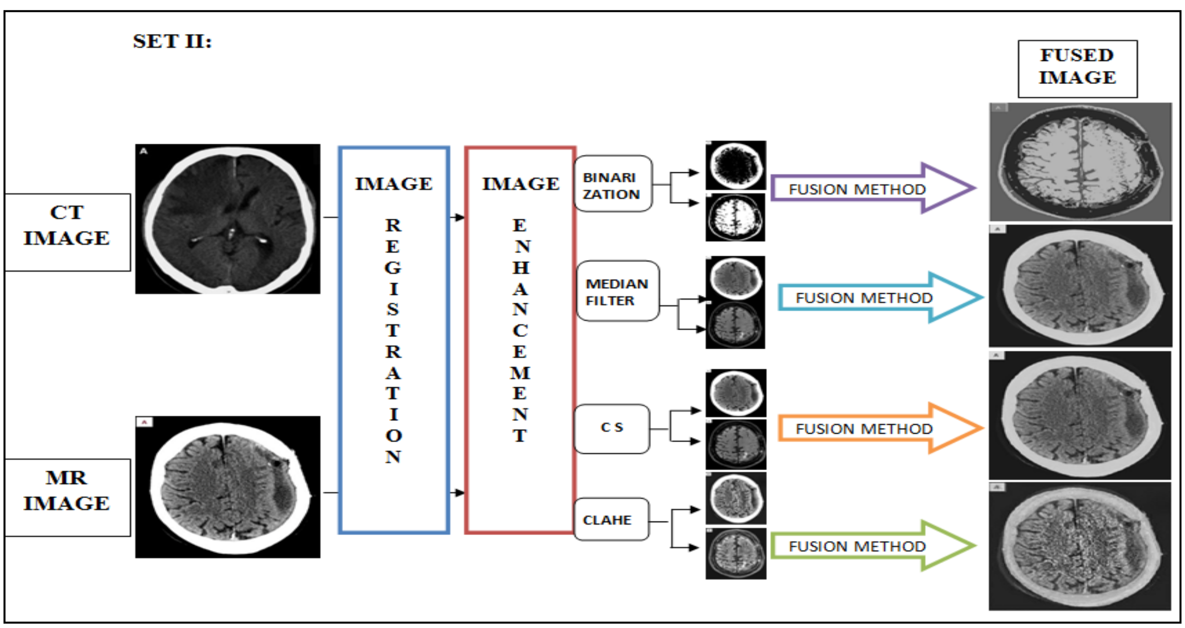


Fig.4.6: Resultant enhanced and fused images for SET II.

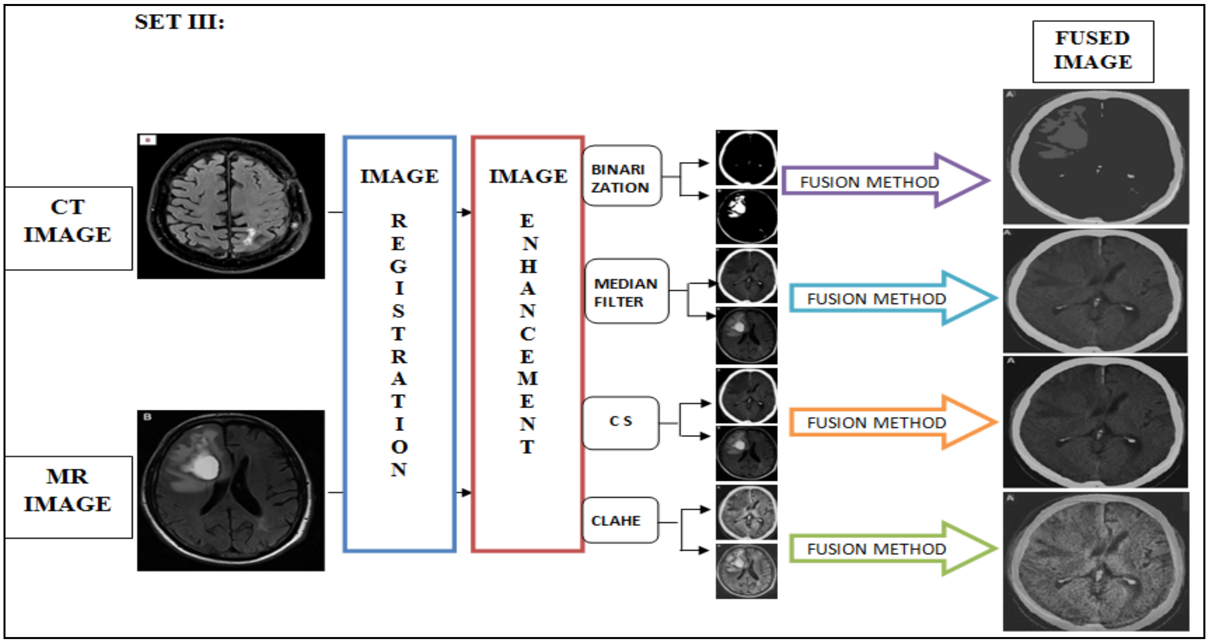


Fig.4.7: Resultant enhanced and fused images for SET III.

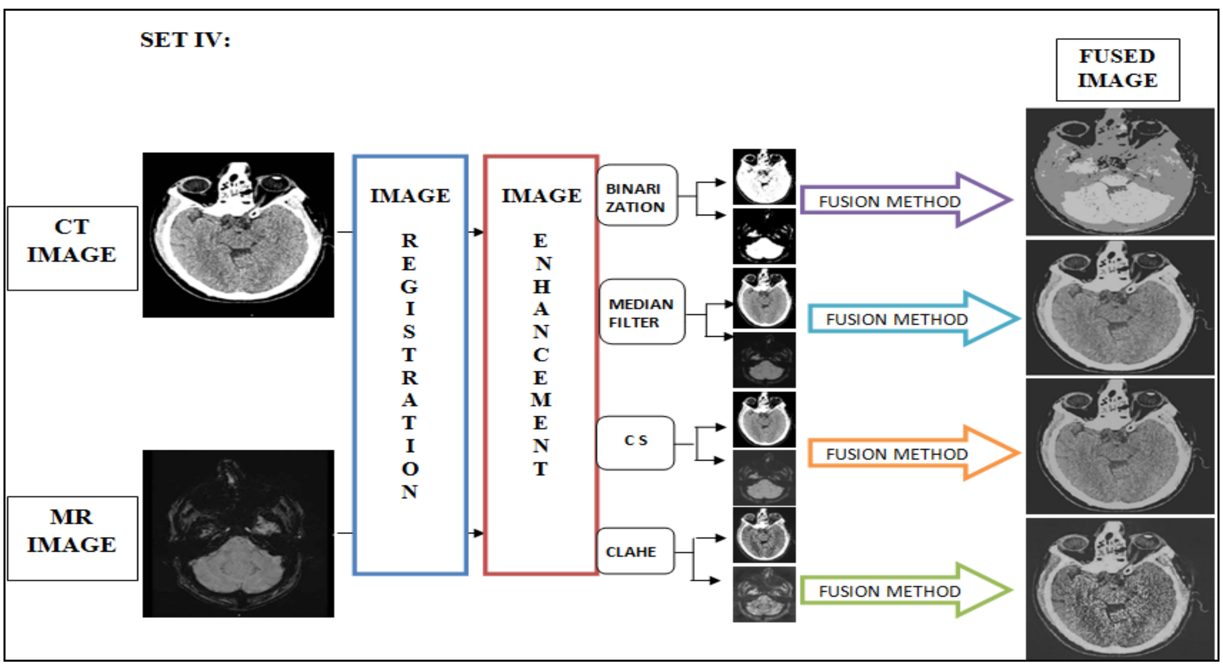
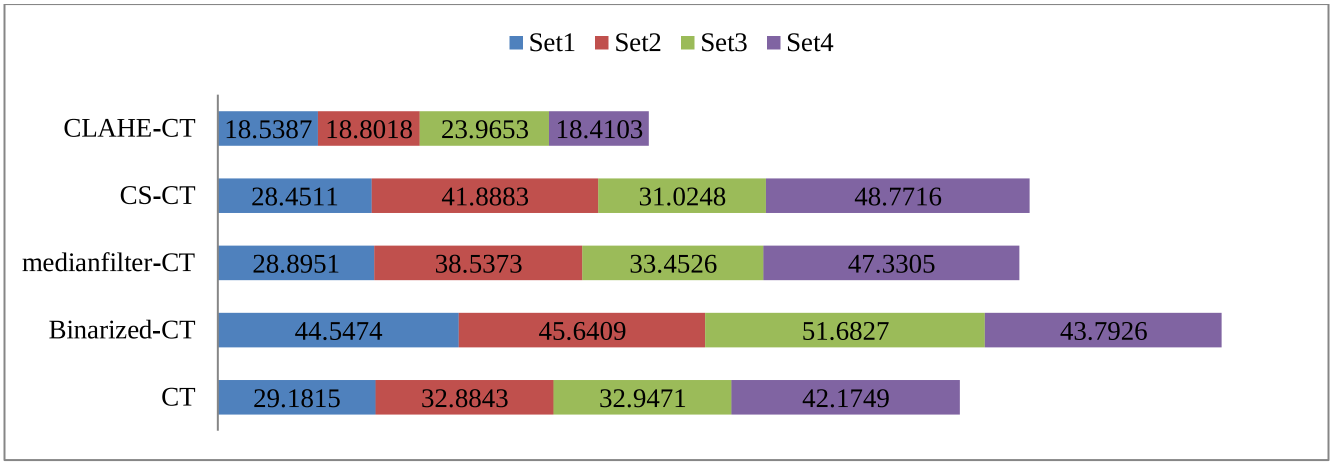


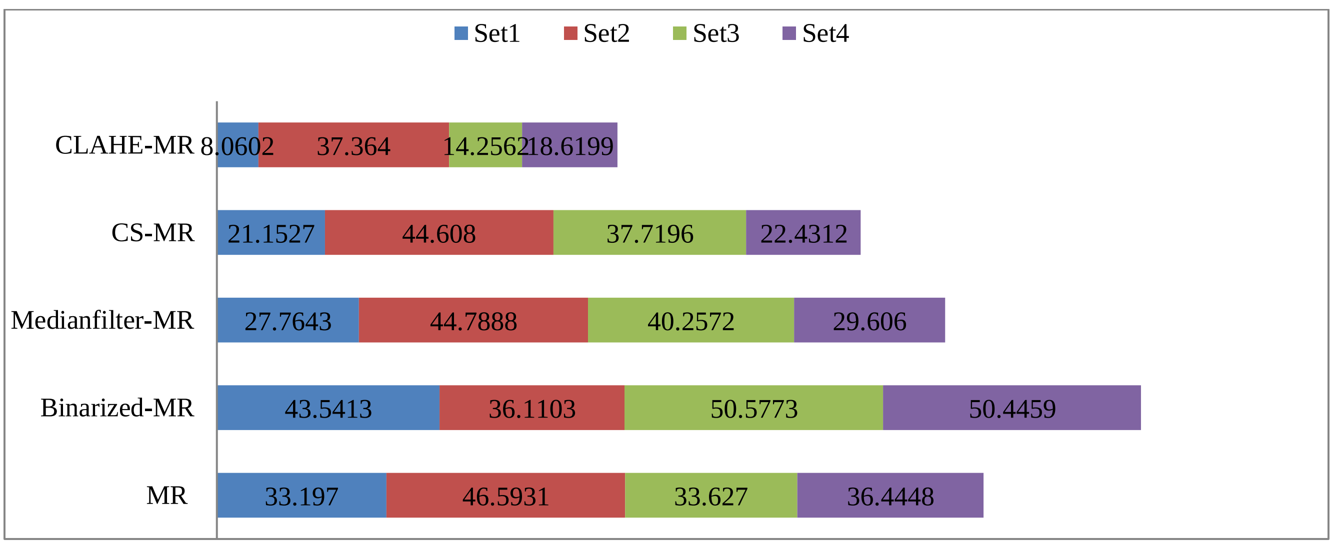
Fig.4.8: Resultant enhanced and fused images for SET IV.

CLAHE outperforms the other approaches based on the experimental results shown in Graph 1 and Graph 2. When comparing the aforementioned fusion algorithms in Table 4.1, it is clear that the hybrid fusion technique provides better PSNR, SNR, and SSIM values. In the table, R1 denotes the first input image, R2 denotes the second input image, and F denotes the final fused image.

Graph 4.1: Comparative analysis of CT images (b/w original image and enhanced image) based on brisque.



Graph 4.2: Comparative analysis of MR images (b/w original image and enhanced image)based on brisque.



When examining the individual CT-MR graphs, it is clear that CLAHE enhanced images produce lower brisque values, indicating that the source images were of poor perceptual quality to begin with. Contrast stretching (CS) values, on the other hand, behave similarly to median filter and binarization in some situations. The findings obtained from the other three, on the other hand, were not persuasive in the sense that the values were inconsistent. As a result, the CLAHE images are processed using the PCA, DWT, and PCA-DWT fusion models.

Table 4.1: Performance Comparison of fusion techniques on the basis of PSNR, SNR and SSIM.

Set No.	Fusion Methods	Performance Metrics					
		PSNR (b/w R1 AND F)	**PSNR (b/w R2 AND F)**	**SNR (b/w R1 AND F)**	**SNR (b/w R2 AND F)**	**SSIM (b/w R1 AND F)**	**SSIM (b/w R2 AND F)**
SET 1	**PCA**	13.13	9.28	13.09	9.25	0.28	0.33
	DWT	16.98	16.97	16.95	16.94	0.49	0.31
	LRD	**20.85**	**19.51**	**20.82**	**19.48**	**0.62**	**0.54**
SET 2	**PCA**	13.92	7.65	13.89	7.62	0.23	0.16
	DWT	14.66	14.71	14.63	14.67	0.53	0.20
	LRD	**20.69**	**15.55**	**20.65**	**15.51**	**0.85**	**0.17**
SET 3	**PCA**	10.67	8.36	10.63	8.32	0.20	0.28
	DWT	16.98	17.02	16.94	16.98	0.50	0.45
	LRD	**23.82**	**17.05**	**23.78**	**17.01**	**0.81**	**0.58**
SET 4	**PCA**	13.33	11.36	13.29	11.32	0.40	0.29
	DWT	15.91	14.31	15.88	14.28	0.34	0.45
	LRD	**17.74**	**15.87**	**17.71**	**15.84**	**0.56**	**0.43**

On the basis of PSNR, SNR, and SSIM, PCA-DWT outperformed the other two fusion methods, owing to the complex but efficient mechanism involved. This can be seen in the Table 4.1 above. The main goal of this project is to explore and compare various enhancement and fusion techniques that can help with contrast enhancement and noise suppression in biomedical images. In light of this, the experimentation in this project has been divided into two sections. The first half of the film examines various enhancement methods. In order to comprehend the output of each for specific sets of CT-MR images, traditional methods such as binarization, median filter, and contrast stretching are considered, as well as commonly used methods such as CLAHE.

The values, for example, in SET III, the brisque value for the original source CT image is 32.94, which is less than 51.68 obtained in binarization, according to chapter 4, Graph 1, which focuses on the experimental values of the CT images This means that while this approach can be useful in some cases, it will yield poor results in cases where the background and region of pixels are unbalanced. The median filter has a value of 33.45, which is higher, and contrast stretching has a numeric value of 31.08, which is lower, but CLAHE approach is found to be more effective as compared to 23.96.

4.4 Conclusion

Due to the imprecision of the image data, doctors can diagnose patients incorrectly. As a result, there is a need for the advancement of a model that can be used to render more accurate clinical decisions, resulting in the proper diagnosis and treatment of diseases. Since there are several factors that influence the quality of source images, enhancement techniques such as CLAHE and image fusion methods such as PCA-DWT can be used to enhance the visual appearance of images. The approach chosen has a significant impact on the final result. As a result, problems such as poor lighting or contrast, blurring, and lack of focus on the image will be reduced. Nonetheless, the project's goal is reached by determining that the CLAHE and PCA-DWT approaches are effective and can be used for further study.

CHAPTER 5

IDENTIFICATION OF CEREBROVASCULAR DISEASES USING CWCT AND FEATURE EXTRACTION

Cerebrovascular disorder is the leading cause of neural mortality rates in adults, with ischemic stroke contributing for the vast majority of cases worldwide. Stroke, also known as cerebrovascular disease, is a noncommunicable disease majorly affecting the elderly population. The term "stroke" refers to a neurological deficit caused by an acute focal damage to the central nervous system caused by a vascular cause, such as cerebral infarction, intracerebral or subarachnoid hemorrhage. The underlying cause of strokes in majority of cases may be detected by a proper history taking, an adequate general evaluation and judicious use of investigations. Since the affected region of the brain cannot survive, the effects of a stroke are extreme long-term frailty or death. With over 1.2 billion people, India has experienced remarkable economic and demographic shifts in recent years, resulting in a shift away from poverty-related infectious and nutritional deficiency diseases and toward lifestyle-related cardiovascular and cerebrovascular diseases[43]. Due to urbanization, and increased exposure to major risk factors would exacerbate the stroke burden in South Asian countries in the future. Also, as the majority of studies are conducted on populations from developed countries, further studies from developing countries such as India are needed to obtain corresponding statistics.

Clinical image processing may be useful for diagnosis and treatment purposes of Cerebrovascular diseases. Because of technological innovation, healthcare facilities must store vast amounts of data in their database which makes data interpretation a difficult task. Image fusion techniques and machine learning algorithms are used to solve a variety of problems in medical centers while managing and analyzing data. The techniques and algorithms aid in establishing a framework and derivation of essential conclusions from the dataset. Therefore, based on the analysis of previous chapters, this section represents a framework for the identification of stroke diseases affecting the brain from multimodal medical images.

5.1 Overview of Proposed Framework

The proposed framework is divided into two phases. In the initial phase, performance of proposed techniques on enhanced medical images (as discussed in Chapter 3 and 4) are compared with the fusion performance of traditional methods. In order to locate the diseases represent, using much fewer data points, feature extraction is utilized. By employing machine learning methods like KNN and SVM classifier, identification of insightful features from the data are classified. Lastly, the efficacy of the framework is affirmed with the aid of few performance metrics based on precision and accuracy. **Fig.5.1** showcases a general outline of the proposed framework.

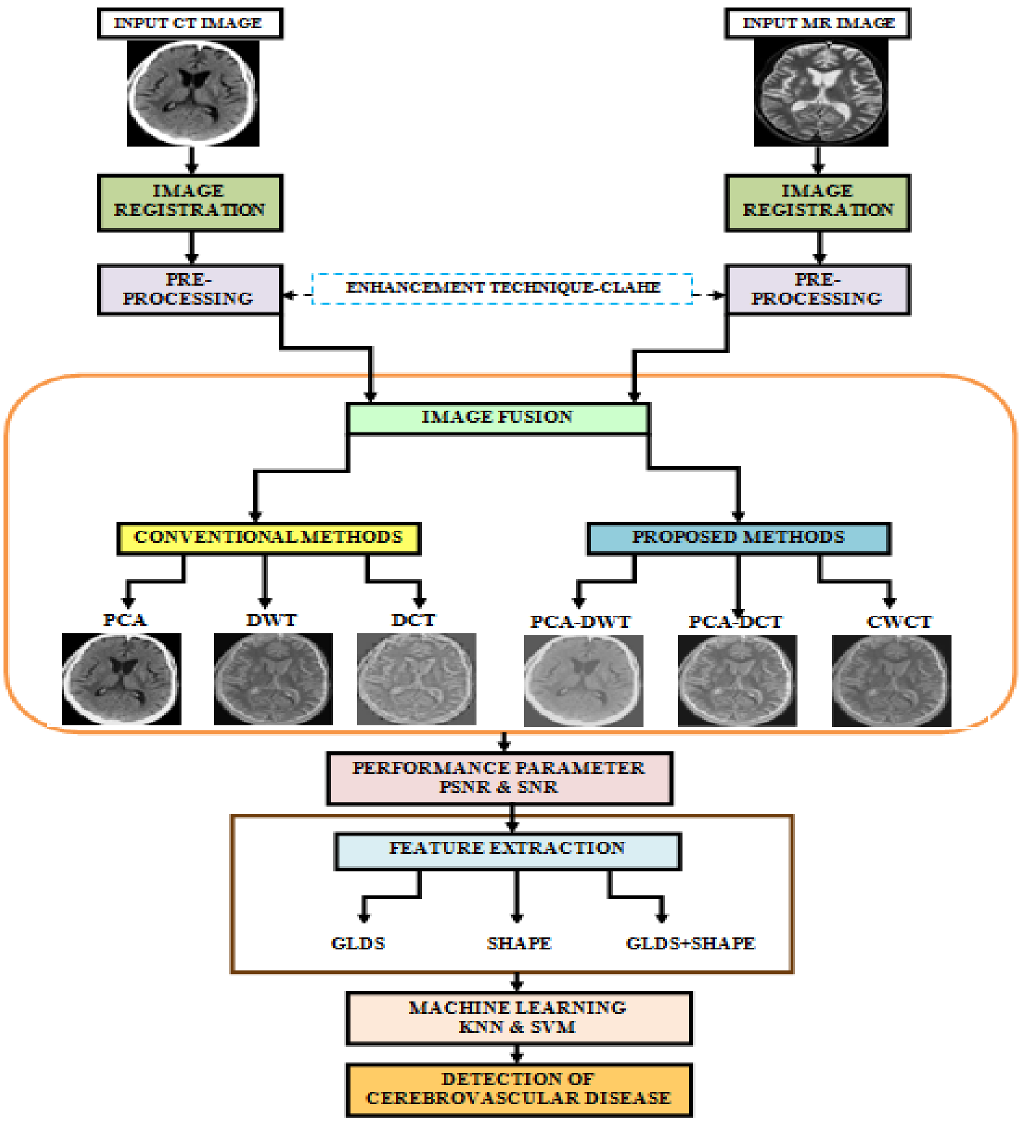


Fig.5.1 A general outline of the proposed framework.

5.1.1 Feature Extraction

Feature extraction is the method of converting raw pixel values from an image into a collection of features, which are usually distinguishing properties of input patterns that can be used in selection and classification tasks. Features are properties that define the entire image. It may also refer to a critical piece of information that is essential for completing a computational task related to a particular application. The method of representing particular sections of data using much fewer data points than were present in the original signal is the main purpose of this method [44]. The information retained on the data after feature extraction is determined by the feature extraction method used. Traditional machine learning methods can be used to predict and identify new data after extracting insightful features from the data [45].The aim of feature extraction is to minimize the size of the original dataset by measuring specific features. The extracted features serve as input to the classifier by taking into account the definition of relevant image properties in feature space. Geometrical, mathematical, model-based, and signal processing feature extraction techniques are commonly used. There are two ways of extracting features: (i) Texture-based and (ii) Morphological Features.

Morphological feature extraction eliminates the background noise from an image before performing segmentation and an examination of shape, scale, and texture. Texture is described as a picture that depicts the structure of the surfaces it represents. The texture property can be indicated using the key features, and the information is saved in the knowledge base for device training [46] [47]. This stage entails extracting essential features from medical anatomies. Some features that are difficult to identify can be derived using FE techniques including statistical methods. This includes first order, Gray Level Difference Statistics (GLDS), the Gray Level Run Length Matrix (GLRLM), and the Gray Level Co-occurrence Matrix (GLCM) as shown in Table 5.1. Transform domain approaches; on the other hand, includes discrete wavelet transform Gabor wavelet, etc. The proposed framework extracts the GLDS statistical texture features [48]. To measure the texture coarseness of the stroke area, the GLDS emphasizes the histogram of the absolute differences in gray level between two pixels separated by a displacement vector.

Table 5.1: Statistical texture features used for feature extraction.

Statistical Attributes	First order statistics	GLCM	GLRM	GLDS
Attributes	Third Moment, Smoothness, Uniformity, Mean, Standard Deviation, Entropy	Contrast, Correlation, Homogeneity, Energy, Entropy, Symmetry, And Moment 1,2,3,4.	Long Run Emphasis, Gray Emphasis, Low Gray Level, Short Run Emphasis, Short Run Low Gray Emphasis, etc	Homogeneity, Contrast, Energy, Entropy, Mean

5.1.2 Classification based on Machine Learning

A brief introduction to classifiers and machine learning algorithms, accompanied by a description of the two methods used in the framework, KNN and SVM is discussed. These two approaches are extremely relevant in this dissertation since they seek to examine and identify complex cerebrovascular diseases using GLDS features. Classification is one of the major machine learning applications that involves the creation of a decision procedure based on a sequence of cases. Classifiers are built based on pre-observed information derived from example data. To achieve a good classification, information from the features of the items under consideration is used and compared to information from the training collection.

a) **SVM Classifiers**: Support Vector Machine(SVM)is a binary classifier that can be used in a variety of research fields. When compared to most conventional classifiers, it is capable of classifying unknown samples with a high degree of accuracy. This algorithm is distinguished by the fact that, rather than attempting to estimate the density likelihood of the classes, it solves the relevant problem directly, i.e. finding the decision surfaces that describe the classes, known as classification boundaries[49].The underlying concept is as follows: given two classes of multidimensional patterns, the SVM determines the hyper-plane that best distinguishes the classes, i.e. it correctly classifies patterns from both classes by maximizing the marginal distance between the classes. In this dissertation, the SVM classification is with the aid of RBF- kernel [50].

b) KNN: The k-nearest neighbor (KNN) algorithm is a technique for classifying objects in pattern recognition or classification that is based on the closest training examples in the problem space. KNN is an instance-based learning or lazy learning method in which the function is only approximated locally and all computation is postponed until classification[51][52]. The k-nearest neighbor algorithm is one of the most basic machine learning algorithms: an object is categorized by a majority vote of its neighbors, with the object assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k is equal to one, the object is simply assigned to the class of its closest neighbor.

5.2 Results and Discussion

This section expands on and correlates the findings obtained for detection of cerebrovascular diseases using four different and two proposed image fusion techniques. The obtained results given in **Fig.5.2** enable us to investigate the capabilities of the medical fusion algorithm when applied to multi-modality images. Enhancement technique improves the contrast and retains the edges of the low quality anatomical images. This section delves further into the findings after comparing the fusion performance of each method considered on the basis of few performance metrics, as shown in Table 4. Due to limitation of space only few sets of CT-MR images are presented. MATLAB is used to implement and simulate the proposed framework**.** The images studied have been taken from the Harvard medical database [53].

SET A depicts a patient who has been diagnosed with a Myocardial Infarction, along with the fused findings obtained from the proposed and other fused techniques. **SET B** describes a patient who has died as a result of a catastrophic stroke, with subsequent fused outcomes from proposed and other fused techniques. **SET C** depicts a portion of the left hemisphere with a large region of irregular lesion that resulted in an acute stroke. The related fused results from the proposed and other fused techniques are also seen. **SET D** depicts a patient with several embolic infarcts and the subsequent fused outcomes obtained from the proposed and other fused techniques.

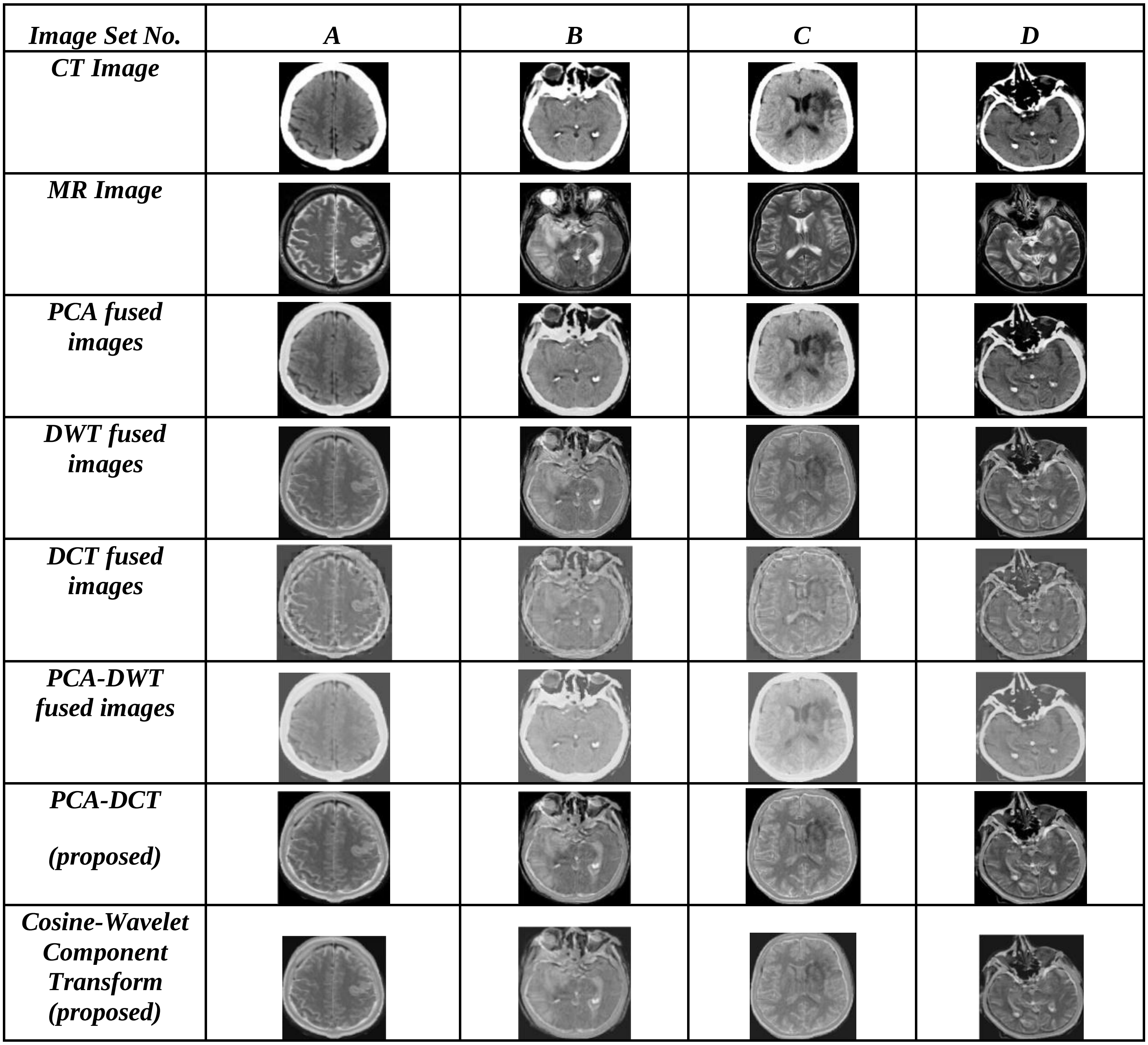


Fig.5.2: Resultant fused images.

There are two types of medical image fusion assessment methods: subjective evaluation and objective evaluation. Subjective assessment, also known as visual evaluation, is performed by looking at the accuracy of the fused images through the naked eye. PSNR 1 and SNR 1 are the experimental findings between source image 1 and the corresponding fused image in Table 5.2.

Table 5.2: Experimental values of performance metrics.

IMAGE SET	PERFORMANCE METRIC (dB)	PCA	DWT	DCT	PCA-DWT	PCA-DCT (proposed)	***Cosine- Wavelet Component Transform* (proposed)**
SET A	PSNR 1	22.59	14.04	13.32	13.38	14.12	**19.64**
	PSNR 2	9.85	14.04	12.29	13.54	14.01	**19.68**
	SNR 1	22.55	14.00	13.28	13.35	14.08	**1961**
	SNR 2	9.81	14.01	12.26	13.50	13.98	**19.64**
SET B	PSNR 1	28.14	14.07	13.21	13.13	14.12	**19.86**
	PSNR 2	9.01	14.09	12.15	13.44	14.12	**19.57**
	SNR 1	28.11	14.04	13.18	13.09	14.09	**19.82**
	SNR 2	8.98	14.06	12.12	13.40	14.09	**19.53**
SET C	PSNR 1	22.70	13.26	12.59	12.35	13.33	**19.52**
	PSNR 2	8.93	13.27	11.80	12.56	13.33	**19.80**
	SNR 1	22.67	13.23	12.55	12.31	13.30	**19.49**
	SNR 2	8.90	13.24	11.77	12.53	13.30	**19.79**
SET D	PSNR 1	23.84	14.36	14.74	14.37	14.43	**18.90**
	PSNR 2	10.01	14.36	11.35	14.92	14.43	**18.85**
	SNR 1	23.81	14.33	14.71	14.34	14.39	**18.86**
	SNR 2	9.98	14.32	11.32	14.89	14.39	**18.81**

Similarly, PSNR 2 and SNR 2 reflect the experimental results for all datasets between source image 2 and the corresponding fused image. SNR is a metric for calculating a fused image's information-to-noise ratio. The greater the value, the more similar the reference and fused images are, while PSNR is a standard metric determined by dividing the number of grey levels in the image by the pixel values in the source and fused images. When the value is strong, the fused and reference images are similar. A higher value indicates improved fusion. As compared to other current traditional techniques, the proposed hybrid methodology outperforms them in terms of performance metrics. In SET C , the performance of PCA and DCT fusion with PSNR 2 values of 8.90 and 11.80 was not satisfactory. The corresponding values 13.37dB, 12.56dB, and 13.33dB for DWT, PCA-DWT, and PCA-DCT, respectively, produced improved but not satisfactory fusion performance.

The Cosine-Wavelet Component Transform, on the other hand, generated the highest experimental value of 19.80dB. Consequently, both numerical and subjective assessment criteria show that the proposed method of multimodal medical image fusion, the Cosine-Wavelet Component Transform, is more accurate. Following fusion, various statistical features are assessed. In this dissertation, attributes concerning only GLDS were analyzed, and their respective experimental values are as shown in Table 5.3.

Table 5.3: Evaluation values of statistical GLDS attributes.

5	6	7	8	9	10
0.28	0.30	0.27	0.30	0.26	0.44
252.97	157.39	220.47	358.10	248.63	115.43
0.07	0.10	0.09	0.09	0.08	0.17
3.22	2.76	2.98	3.07	2.99	2.26
9.42	5.98	7.59	8.98	7.60	3.91
513.00	52879.00	51932.00	40977.00	52275.00	177550.00
1023.41	1132.81	1499.30	2840.96	1703.75	3249.74
25.56	259.48	257.14	228.42	257.99	475.46
-281.00	-135.00	-27.00	-236.00	-90.00	-147.00
2.00	2.00	5.00	2.00	2.00	2.00
418.86	262.72	264.33	268.21	266.85	487.51
209.44	256.57	254.45	224.85	250.78	465.43
0.87	0.22	0.27	0.55	0.34	0.30
-45.00	-87.33	-84.95	-4.29	77.46	-46.80
33153.00	53677.00	54728.00	60430.00	57957.00	201105.00
0.01	0.81	0.80	0.63	0.82	0.80

Image Serial No.	1	2	3	4
Parameters				
Homogeneity	0.09	0.19	0.21	0.23
Contrast	527.06	336.51	285.06	322.81
Energy	0.03	0.05	0.05	0.05
Entropy	3.69	3.46	3.38	3.40
Mean	14.70	11.41	10.58	11.05
Area	307.00	1241.00	256.00	512.00
perimeter	539.36	1445.20	510.00	1021.41
Diameter	19.77	39.75	18.05	25.53
eular no	-163.00	-328.00	200.00	194.00
solidity	3.00	3.00	1.00	4.00
Majoraxis	268.72	340.27	295.60	418.05
MINORAXIS	3.99	172.60	1.15	209.02
Eccentrycity	1.00	0.86	1.00	0.87
Orientation	-89.97	-33.21	0.00	-44.78
ConvexArea	895.00	33895.00	256.00	32974.00
Extent	0.20	0.02	1.00	0.01

Furthermore, texture-based analysis is used to detect the form of brain strokes or Cerebrovascular disease in the resulting images, which contributes to the extraction of useful features. The algorithm gathered a total of 56 features, including twenty texture features and 42 shape features, which were then used to evaluate performance and feed the collected statistics to KNN and SVM classifiers. The focus of this work has been on exploring the characteristics of GLDS features and shape-based descriptors. Table 5.4 shows the details of the features extracted (based on Cosine-Wavelet Component Transform fused images) by statistical analysis of the MR and CT images.

The results show that the obtained features Homogeneity, Mean, Contrast, Energy, and Entropy provided superior values as compared to other methods. In this analysis, all of the features were used in the classification process, which was done with KNN and SVM. KNN is solely dependent on its neighbors. It doesn't even need a training period. The goal class is the one with the most neighboring neighbors. KNN is more intuitive, but it may be slower to use if K's value is held high or the total number of points is large. Table 5.4 compares the classification accuracy of various fusion techniques using GLDS, form, and a combination of GLDS and shape features using KNN.

Table 5.4: Comparison on accuracy of classification of GLDS attributes.

	Cosine-Wavelet Component Transform			**DWT- PCA**			**PCA-DCT**		
Different *k*-values → **↓ Different features**	**3**	**4**	**5**	**3**	**4**	**5**	**3**	**4**	**5**
GLDS	80	90	60	80	80	80	77	77	80
Shape	70	80	70	90	90	90	70	70	40
GLDS + Shape	80	**92**	80	90	90	90	90	90	90

Cosine-Wavelet Component Transform for k = 4 with a combination of function GLDS and shape achieves maximum accuracy of 92 percent. The KNN technique is slower and performs poorly in high-dimensional spaces. One of the main reasons KNN is sluggish is that it involves directly inspecting the training data elements during assessment. A naive KNN classifier considers all data points to make a single prediction, while many machine learning methods do not rely on the number of training data points for evaluation run time. KNN's approach to understand nonlinear problems in lower dimension spaces with so much ease is remarkable, but the duration (and performance) on greater and higher dimensional problems is undeniably a disadvantage. In high-dimensional spaces, efficiency suffers because the distance between points becomes less important as a quantity.

SVM is used for further processing to address the drawback of using KNN. The SVM looks for a hyperplane that separates data points from various groups. The SVM's goal is now to find the hyperplane that maximizes the margin between the data points and itself. Utilizing kernel methods, the SVM can be generalized to be a non-linear classifier. However, determining which kernel is best for a given problem is difficult. To optimize the algorithm in the Support Vector Machine, different parameters, namely the kernel, Gamma parameter, and C parameter, must be chosen. The table shows the consistency when various parameters are taken into account when using the LiBSVM library. Both fusion techniques were simulated, but Table 5.5 computes the findings of proposed image fusion techniques using SVM.

Table 5.5: Experimental values of proposed framework.

		Nu	Obj	rho	nSV	nBSV	Accuracy
Cosine-Wavelet Component Transform	**Shape features**	0.705	-3026.10	-0.158	10	5	81.81%
	GLDS features	0.002917	-262.841	2.916	7	0	95%
	GLDS + Shape features	0.000296	-26.684	0.425	11	0	98%
DWT + PCA	**Shape features**	0.000036	-3.277636	-0.027	8	0	90%
	GLDS features	0.563009	-4882.552	0.048	8	6	95%
	GLDS + Shape features	0.000035	-3.119	-0.059	10	0	96%
DCT + PCA	**Shape features**	0.000564	-50.835	-0.141	11	0	85%
	GLDS features	0.000399	-35.914	1.473	4	0	87%
	GLDS + Shape features	0.409768	-6608.737	0.785	7	3	90.91 %

As observed from Table 5.5, where obj stands for the optimal objective value of the dual SVM problem, rho stands for the bias term in the decision function sgn(wT x - rho), nSV stands for the number of support vectors, and nBSV stands for the number of bounded support vectors (I = C). Nu-SVM is a structure similar to C-SVM in which C is replaced by nu. For a large value of C, the model considers more support vector data points to obtain a higher variance and lower bias, resulting in an overfitting problem. If the value is low, it chooses less data points as a support vector and has a low variance or high bias. The proposed image fusion technique achieves the highest level of precision by combining GLDS and shape-based features. The proposed Cosine-Wavelet Component Transform achieves 98 percent accuracy, DWT + PCA achieves 96 percent accuracy, and DCT + PCA fusion method achieves 90.91 percent accuracy. The Cosine-Wavelet Component Transform and DWT + PCA fusion techniques achieve 95 percent accuracy using GLDS features, while the DCT + PCA fusion technique achieves 87 percent accuracy. Form features achieve 81.81 percent, 90 percent, and 85 percent precision for all three proposed fusion techniques.

CHAPTER 6

CONCLUSION AND FUTURE WORK

Conclusion: Medical imaging has proved beneficial for better diagnosis and treatment by classifying images and detecting ailments that are otherwise difficult to detect with current technology. This work's proposed framework has been developed, implemented, and assessed. The research is inspired primarily by the possibility and assurance of accurately localizing diseases from better quality anatomical images with the aid of image fusion technologies in multimodal medical systems and applications. We investigated various techniques such as image fusion, enhancement methods, utilization of feature extraction and classifying methods like KNN and SVM. We tested and demonstrated the proposed framework using multi-modal images. Our approach is simple to implement, allowing us to use comprehensive approaches to medical systems.

Using performance criteria, we demonstrated a comparative analysis of the results obtained by traditional and novel fusion methods. Our proposed methodology, Cosine-Wavelet Component Transform produces much better image fusion results at a low computational cost while maintaining image clarity based on different performance metrics.. In this thesis, the fused images were used to remove various morphological and GLDS features, which were then used to detect Cerebrovascular disease using various data mining techniques. The effectiveness of each is then validated using feature extraction, which extracts prominent features of the lesion and then uses them as inputs to classifiers to apply them to the group that they represent.

Future Work: Each algorithm has its own set of limitations as well as advantages. The future research directions will be geared toward further development of our proposed methodology, which will yield higher qualitative and low error values along with the exploration of data mining techniques

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