VISVESVARAYA TECHNOLOGICAL UNIVERSITY
Jnana Sangama, Belagavi - 590 018

PROJECT REPORT ON

Image Registration Using Convolutional Neural Network For Brain Tumor Detection

Thesis submitted in partial fulfillment for the Award of Degree of
Bachelor of Engineering
in
Electronics and Communication Engineering

Submitted by

Chandan M Shekar	1RN16EC188
Manoj Raj M	1RN16EC191
Vinay R	1RN16EC190
Naveen Rao V	1RN17EC418

Under the Guidance of
Leena Chandrashekar
Assistant Professor

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
(Accredited by NBA for the Academic years 2018-19, 2019-20 and 2020-21)

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Channasandra, Dr.Vishnuvardhan Road, Bengaluru-560098

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CERTIFICATE

Certified that thesis work entitled **"Image Registration Using Convolutional Neural Network For Brain Tumor Detection "** is carried out by **Chandan M Shekar, Manoj Raj M, Vinay R, and Naveen Rao V** in partial fulfillment for the award of Bachelor of Engineering in **Electronics and Communication Engineering** of Visvesvaraya Technological University, Belagavi, during the year 2019-2020. It is certified that all corrections / suggestions indicated for internal assessment have been incorporated in the report. The project report has been approved as it satisfies the academic requirements in aspect of the project work prescribed for the award of degree of **Bachelor of Engineering**.

....	....	....
Leena Chandrashekar	Dr. Vipula Singh	Dr. M K Venkatesha
Assistant Professor	Head of Department	Principal

External Viva

Name of the examiners	**Signature with date**
1	....
2	....

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DECLARATION

We here by declare that the entire work emobodied in this project report titled, **"Image Registration Using Convolutional Neural Network For Brain Tumor Detection"** submitted to **Visvesvaraya Technological University**, Belagavi, is carried out by us at the department of **Electronics and Communication Engineering** RNS Institue of Technology, Bengaluru under the guidence of **Leena Chandrashekar**, Assistant Professor. This report has not been submitted in part or full for the reward of any Diploma or degree of this or any other university.

Name	USN	Signature
1.Chandan M Shekar	1RN16EC188	....
2.Manoj Raj M	1RN16EC191	....
3.Vinay R	1RN16EC190	....
4.Naveen Rao V	1RN17EC418	....

Abstract

Quantitative analysis of many neurological diseases depends on automated and accurate registration of medical structures. Nowadays, the neural networks based registration methods have gained interest of research because of their self-learning capabilities over huge amount of dataset. The role of these processes arises from their ability to help the experts in diagnosis, following up the diseases evolution and deciding necessary therapies based on patients condition. The main aim of this project is to focus on Brain image registration with the help of convolutional neural network and detection of accurate tumor region by DWT-PCA image fusion and Threshold Segmentation method . Registration is based on the features extracted from the image, a large amount of data is analyzed to obtain processing results. Focusing on image feature extraction based on convolutional neural network, the customized framework of CNN is built. The proposed end-to-end convolutional neural network approach aims to predict fields to align multiple labeled corresponding structures for individual image pairs during the training. At inference, the resulting image registration algorithm runs in real-time and is fully-automated. The proposed end-to-end convolution neural network approach aims to predict the Angle of Rotation of given CT/MRI Brain image and based on tumor positive and negative, it highlights the region of tumor existence.

Acknowledgement

The joy and satisfaction that accompany the successful completion of any task would be incomplete without thanking those who made it possible. We consider ourselves proud to be a part of RNS Institute of Technology, the institution which molded us in all our endeavors.

We express our gratitude to our beloved Chairman **Dr. R N Shetty**, for providing state of art facilities.

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We express our profound gratitude to the coordinators who have given valuable suggestions and guidance throughout the project. We would like to express our sincere gratitude to internal guide **Leena Chandrashekar**, Assistant Professor for her guidance, continuous support and motivation in completing the project successfully. We are also thankful to all the teaching and non-teaching faculty of RNSIT for their constant support.

Chandan M Shekar
Manoj Raj M
Vinay R
Naveen Rao V

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Acronyms

1. CNN: Convolutional Neural Network
2. SGDM: Stochastic Gradient Descent With Momentum
3. ADAM: Adaptive Moment Estimation
4. CT:Computerized Tomography
5. MRI:Magnetic Resonance Imaging
6. DWT:Discrete Wavelet Transform
7. PCA:Principle Component Analysis
8. IHS:Intensity-Hue-Saturation
9. ReLU: Rectified Linear Unit
10. GPU: General Purpose Unit
11. RGB: Red-Green-Blue
12. MATLAB: Matrix Laboratory
13. SVM: State Vector Machine
14. PSNR:Peak Signal To Noise Ratio
15. MSE: Mean Square Error
16. SSIM:Structural Similarity Index
17. BMP:Bitmap
18. HDF: Hierarchical Data Format
19. JPEG: Joint Photographic Experts Group
20. PCX: PiCture eXchange
21. TIFF: Tag Image File Format
22. XWB:eXtra Wide Body

Chapter 1

Introduction

Within the current clinical setting, medical imaging is a vital component of a large number of applications. Since information gained from two images is usually of a complementary nature, proper integration of useful data obtained from the separate images is often desired. A first step in this integration process is to bring the modalities involved into spatial alignment, a procedure referred to as registration. In view of this we perform pattern feature extraction of tumor image. As the image shifts and rotation changes,the image is stationery relative to co-ordinate system. The method then can accurately describe the tumor image,thereby increasing the robustness of the image description. After registration, a fusion step is required for the integrated display of the data involved. An example of , the use of registering different modalities can be found in radiotherapy treatment planning, where currently CT is used almost exclusively. However, the use of MRI and CT combined would be beneficial, as the former is better suited for delineation of tumor tissue (and has in general better soft tissue contrast), while the latter is needed for accurate computation of the radiation dose.

1.1 Objectives

1. To perform image registration of brain tumor using convolutional neural network by automatic feature extraction.

2. Perform image fusion of CT and MRI scans for better tumor identification.

3. Perform local thresholding and segmenting the tumor part.

4. To provide faster response for registering and classifying untrained images.

5. To overcome problems such as image rotation, that are common when mapping images.

6. To ensure the Trained Network, accurately provides the transformation parameters even if the input image is changed.

1.2 Methodology

Training And Testing Phase

1. Firstly a set of pre obtained original images are trained with the help of convolutional neural networks.

2. The control points in the test images are first extracted. All the features required for comparison are sensed.

3. The features extracted from the trained set of data are compared with the features extracted from the input test image fed by the user.

4. The input image is classified with the trained model, based on the features extracted by neural network.

5. Finally the images are registered based on their similarity with the trained set of images.

6. Further they are classified as tumor positive/negative based on the trained parameters determined by neural network .

7. Once the image is registered and classified as tumor positive direct level thresholding of the images is initiated .

8. In case image is classified as tumor negative, we initiate the fusion of CT and MRI scan images and then continue with segmentation.

9. This process intensifies the features of the shallow layer of tumor image, thereby enhancing the robustness of tumor region.

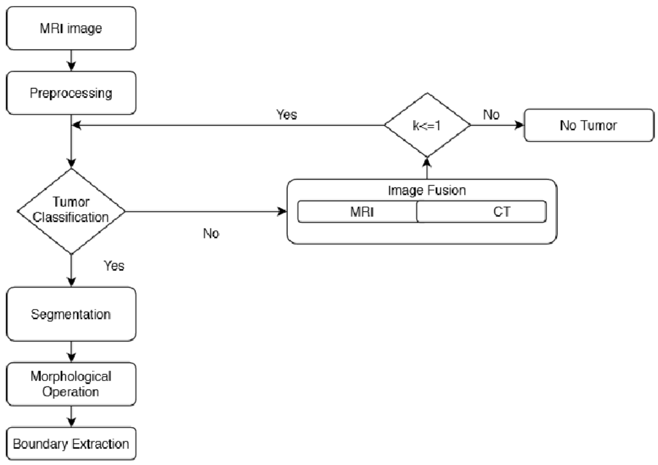

Figure 1.1: Proposed System Block Diagram

1.3 Registration Techniques

Extrinsic Method: In this method artificial foreign objects which are easily detectable are attached to the patient body. They serve as external features to be used for feature matching. The complexity is lessened and hence computational is fast and accuracy is also maintained.
Wavelet Based Method: Wavelet Transform was introduced to get an idea of the time instant at which a particular frequency exists. The width of the window is altered as the transform is computed for each spectral component the most important characteristic of the multiresolution wavelet transform. It offers both time and frequency selectivity.
Correlation Based Method: This method is essentially useful for registration of monomodal images and for comparison of several images of the similar object . It has immense usage in the field of medical sciences for analyzing and treatment of disease. Extracted features from the images are also used to obtain the cross-correlation coefficients for image registration. Cross-correlation and Phase-correlation techniques based on Fourier domain are also used for image registration.
Surface Method: Surfaces or boundaries or contours are generally distinct in medical images unlike landmarks. These surface matching algorithms are generally applied to rigid body registration. A collection of points, generally called a point set is extracted from the contours in an image. The surface covering the larger volume of the patient, or that having a higher resolution is generally considered for generation of the surface model. In this project we have used a new technique for image registration i.e Angle Based Registration. Unlike the older techniques, here images are registered using Convolutional Neural Network.

Table 1.1: Pre-Registration Results

Angle	MSE	STD	ENTROPY
2	97.925	34.68	5.068
10	82.8712	32.9497	4.591
28	61.03	29.365	3.6838
40	56.4057	28.4623	3.4721

Table 1.2: Post-Registration Results

Angle	MSE	STD	ENTROPY
2	84.974	38.434	6.5325
10	61.567	38.302	6.512
28	33.22	37.8066	6.4752
40	28.36	37.7122	6.4623

Chapter 2

Literature survey

ARTICLE 1: Convolution neural network for multimodal image registration by Elseiver B.V

The Methodology of neural network to predict voxel correspondence, Convolution Neural Network to distinguish tumor. The advantage is Cross validation for each network, healthy brain and tumor are analysed using multimedia MRI.

ARTICLE 2: Convolution Neural Network based image detection of abnormalities in MRI Brain Images by P Muthu Krishnammal and S.Selvakumar Raja

The Methodology is Classification using CNN , Acqusition of MRI brain image dataset. The Advantages are Wavelet transform presented, tumor localised accurately, and Disadvantage is inaccurate registration.

ARTICLE 3:Image Registration for early detection by B. Devkota, Abeer Alsadoon, P.W.C. Prasad, A.K. Singh, A. Elchouemi.

The Methodology is Preprocessing- Median filter,Registration done through Mathematical Morphology, Feature extraction by Statistical and textual features Classification-SVM. The Advantages are Better accuracy and lower computational costs in methods of registration and Disadvantage is Not tested with large datasets with abundant variations.

ARTICLE 4:Review on Brain Tumor Detection by O. N. Pandey,Sandeep Panwar Jogi, Sarika Yadav, Veer Arjun, Vivek Kumar

The Methodology is Preprocessing- High pass and Median Filter Morphological operation The Advantages are Two types of processes for better accuracy, and Disadvantages are Manual intervention is needed, low accuracy.

ARTICLE 5: Brain Tumor Detection using K-means Clustering by Deepak Agarwal, Vyom Kulshreshtha, Dr. Pankaj Sharma

The Methodology is Preprocessing- Noise filter, Median Filter, image sharpening and enhancing is by Registration through K means clustering. The Advantages are Simplicity and low computational cost, runs efficiently on large datasets, leads to find exact location of tumor, and Disadvantages are Reduce impulse noise only, different results depending on the initial assignment of centroid.

ARTICLE 6: Automated Brain Tumor Detection using Convolution Neural Networks by Priyanka Bedekar, Niharika Prasad, Revati Hagir, Neha Singh

The Methodology is Preprocessing- Noise removal by fourth order partial derivative, image enhancement using histogram equalization, Registration- Conform threshold from Fuzzy Clustering Method Tumor detection.The Advantages are Economical in terms of time and human efforts, simplicity, and Disadvantages are Threshold Is chosen manually, no edge preservation.

ARTICLE 7: Efficient Brain Tumor Detection using Image Processing Techniques by Khurram Shehzad, Imran Siddique, Obed Ullah Memon

The Methodology is Preprocessing- Gaussian low pass filter, median filter Enhancement using morphological gradient like erosion and dilation Tumor extraction. The Advantages are Automated, easy and successful in detection and extraction of tumor from MRI, Threshold selection is automated and Disadvantages are Highly complex, cost of implementation is high.

ARTICLE 8: Brain Tumor detection using Image registration Siddhi N Nerurkar

The Methodology is Preprocessing median filter Registration-K means, region growing. The Advantages are K means is cost effective, region growing is more accurate and Disadvantages are Seed value should be defined initially(region based), final results depends on the assignment of centroids(K means).

ARTICLE 9: Brain Tumor detection using Image registration Samriti, Mr.Paramveer Singh

The Methodology is Contrast,Erosion and dilation, edge preservation, detection using MATLAB. The Advantages are Registration using watershed and contrast methods giving high accuracy and , Disadvantage is Noises are not removed.

ARTICLE 10: Feature extraction techniques for brain tumor detection Vipin Y. Borole, Sunil S. Nimbhore, Dr. Seema S. Kawthekar

The Methodology is Preprocessing- hybrid filter Image enhancement- contrast enhancement Feature extraction- edge detection, threshold, histogram. The Advantages are Preserves global line shapes efficiently, removes speckles and impulse noise and reduces the blurring effect and, Disadvantages are Should find strong image gradient to drive the contour, Lacking accuracy due to weak image boundaries and image noise.

ARTICLE 11: Application of Edge detection for Brain Tumor detection Pratibha Sharma, Manoj Diwakar, Sangam Choudhary

The Methodology is Noise removal- Geometric mean filters and median filters, Laplacian filters and sobel filters for edge detection. Morphological operators- Erosion and Dilation. The Advantages are Noises including gaussian noise is removed, cancerous cells in other organs can also be identified with some modification and, Disadvantages are Over-detection is possible, time consuming.

ARTICLE 12: Image Fusion of CT/MRI using DWT , PCA Methods and Analog DSP Processor Sonali Mane1 ,S. D. Sawant2

The Methodology is Fusion Methods: DWT(Haar wavelet transform), PCA, DWT+PCA method. The Advantages are PSNR is increased as compare to other methods with less MSE, and Disadvantages Depends on the processor used for image processing.

Chapter 3

Matlab Programming Language

MATLAB is a numerical computing environment and programming language. Created by The MathWorks, MATLAB allows easy matrix manipulation, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs in other languages. Although it is numeric only, an optional toolbox interfaces with the Maple symbolic engine, allowing access to computer algebra capabilities.

MATLAB is built around the MATLAB language, sometimes called M-code or simply M. The simplest way to execute M-code is to type it in at the prompt, in the Command Window, one of the elements of the MATLAB Desktop. In this way, MATLAB can be used as an interactive mathematical shell. Sequences of commands can be saved in a text file, typically using the MATLAB Editor, as a script or encapsulated into a function, extending the commands available [3].

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include:

1. Math and computation
2. Algorithm development
3. Scientific and engineering graphics
4. Modelling, simulation, and prototyping
5. Data acquisition, data analysis, exploration, and visualization
6. Application development, including graphical user interface building.

3.0.1 Image Processing Toolbox

Provided in MATLAB it provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development. You can restore noisy or degraded images, enhance images for improved intelligibility, extract features, analyse shapes and textures, and register two images. Most toolbox functions are written in the open MATLAB language, giving you the

ability to inspect the algorithms, modify the source code, and create your own custom functions.
Image Processing Toolbox supports engineers and scientists in areas such as biometrics, remote sensing, surveillance, gene expression, microscopy, semiconductor testing, image sensor design, colour science, and materials science. It also facilitates the learning and teaching of image processing techniques [4].

3.0.2 Digital Images

A digital image is composed of pixels which can be thought of as small dots on the screen. A digital image is an instruction of how to colour each pixel. A typical size of an image is 512-by-512 pixels. It is convenient to let the dimensions of the image to be a power of 2. For example, 29=512. In the general case, we say that an image is of size m-by-n if it is composed of m pixels in the vertical direction and n pixels in the horizontal direction.
Let us say that we have an image on the format 512-by-1024 pixels. This means that the data for the image must contain information about 524288 pixels, which requires a lot of memory! Hence, compressing images is essential for efficient image processing. Fourier analysis and Wavelet analysis can help us to compress an image significantly. There are also a few ”computer scientific” tricks (for example entropy coding) to reduce the amount of data required to store an image. The following image formats are supported by MATLAB:

1. BMP
2. HDF
3. JPEG
4. PCX
5. TIFF
6. XWB

3.0.3 Guide Tool

GUIDE, the MATLAB Graphical User Interface development environment, provides a set of tools for creating graphical user interfaces (GUIs). These tools greatly simplify the process of designing and building GUIs. You can use the GUIDE tools to:

1. Lay out the GUI: Using the GUIDE Layout Editor, you can lay out a GUI easily by clicking and dragging GUI components – such as panels, buttons, text fields, sliders, menus, and so on – into the layout area.

2. Program the GUI: GUIDE automatically generates an M-file that controls how the GUI operates. The M-file initializes the GUI and contains a framework for all the GUI callbacks – the commands that are executed when a user clicks a GUI component. Using the M-file editor, you can add code to the callbacks to perform the functions you want.

3. The GUIDE tool provides various options including Push Button, Radio Button, Check box, Slider, List Box, Pop-up menu, Toggle button and panel.

3.0.4 Hardware Requirements

The project uses the following hardware components:

1. CPU, Intel Dual Core.

2. Hard disk 500GB,RAM 8GB.

Chapter 4

Image Registration

4.1 SURF Extraction

Object Recognition using Speeded-Up Robust Features (SURF) is composed of three steps [1]:

1. Feature extraction
2. Feature description
3. Feature matching.

4.1.1 What Are Local Features ?

Local features refer to a pattern or distinct structure found in an image, such as a point, edge, or small image patch. They are usually associated with an image patch that differs from its immediate surroundings by texture, color, or intensity. What the feature actually represents does not matter, just that it is distinct from its surroundings.

4.1.2 Benefits And Features Of Local Features

Local features let you find image correspondences regardless of occlusion, changes in viewing conditions, or the presence of clutter. In addition, the properties of local features make them suitable for image classification, Local features let you find image correspondences regardless of occlusion, changes in viewing conditions, or the presence of clutter. In addition, the properties of local features make them suitable for image classification. Local features are used in two fundamental ways:

1. To localize anchor points for use in image stitching or 3-D reconstruction.
2. To represent image contents compactly for detection or classification, without requiring image segmentation.

4.1.3 Feature Detection and Feature Extraction

Feature detection selects regions of an image that have unique content, such as corners or blobs. The key to feature detection is to find features that remain locally invariant so that you can detect them even in the presence of rotation or scale change [2].
Feature extraction is a fundamental step in any object recognition algorithm. It refers to the process of extracting useful information referred to as features from an input image. The extracted features must be representative in nature, carrying important and unique attributes of the image. The SurfDetect.m function is the main entry-point, that performs feature extraction. This function accepts an 8-bit RGB or an 8-bit grayscale image as the input. It involves,

1. The Convert32bitFPGray.m function converts an 8-bit RGB image to an 8-bit grayscale image. After this step, the 8-bit grayscale image is converted to a 32-bit floating-point representation for enabling fast computations on the GPU.

2. The MyIntegralImage.m function calculates the integral image of the 32-bit floating-point grayscale image obtained in the previous step. The integral image is useful for simplifying finding the sum of pixels enclosed within any rectangular region of the image. Finding the sum of pixels helps in improving the speed of convolutions performed in the next step.

3. The FastHessian.m function performs convolution of the image with box filters of different sizes and stores the computed responses.

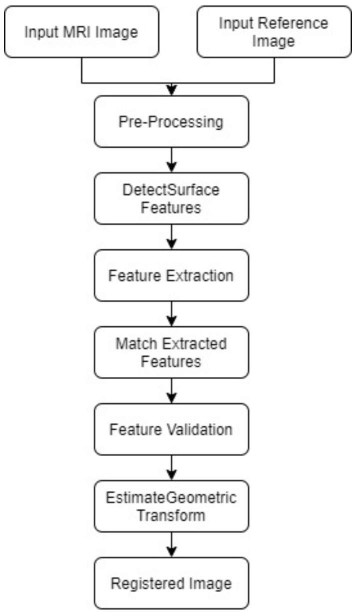

Figure 4.1: Traditional Method: Syetem Architecture

4.2 Convolutional Neural Network

A neural network is a computing model whose layered structure resembles the networked structure of neurons in the brain, with layers of connected nodes. A neural network learns from dataso it can be trained to recognize patterns, classify data, and forecast future events. A neural network combines several processing layers, using simple elements operating in parallel and inspired by biological nervous systems. It consists of an input layer, one or more hidden layers, and an output layer. The layers are interconnected via nodes, or neurons, with each layer using the output of the previous layer as its input. Typically a neural network will break down the input into layers of abstraction[1].

It can be trained over many examples to recognize patterns in speech or images, for example, just as the human brain does. Its behavior is defined by the way its individual elements are connected and by the strength, or weights, of those connections. These weights are automatically adjusted during training according to a specified learning rule until the neural network performs the desired task correctly. Neural networks are especially well suited to perform pattern recognition to identify and classify objects or signals in speech, vision, and control systems [9]. Pathologists rely on cancer detection applications to guide them in classifying tumors as benign or malignant, based on uniformity of cell size, and other factors. Here, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network.

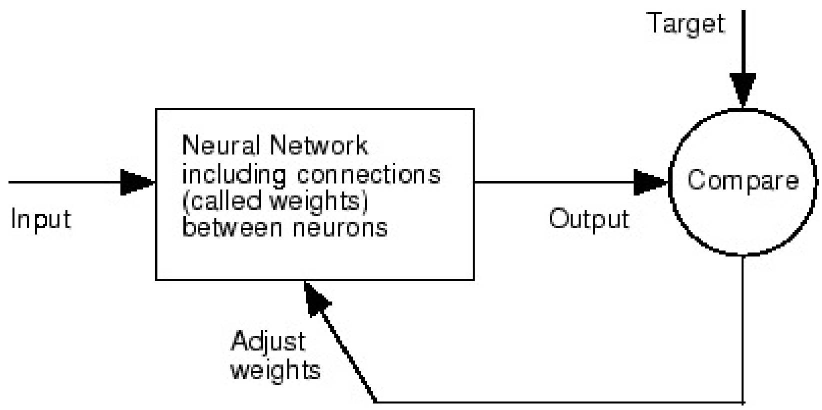

Figure 4.2: Basic Control Block-CNN

4.2.1 Techniques Used With Neural Networks

Common machine learning techniques for designing neural network applications are:

1. Supervised and Unsupervised learning
2. Classification
3. Regression
4. Pattern Recognition
5. Clustering

Supervised Learning
Supervised neural networks are trained to produce desired outputs in response to sample inputs, making them particularly well suited for modeling and controlling dynamic systems, classifying noisy data, and predicting future events[4]. Deep Learning Toolbox includes four types of supervised networks: feedforward, radial basis, dynamic, and learning vector quantization[2].

Classification
Classification is a type of supervised machine learning in which an algorithm learns to classify new observations from examples of labeled data.

Regression
Regression models describe the relationship between a response (output) variable and one or more predictor (input) variables.

Pattern Recognition
Pattern recognition is an important component of neural network applications in computer vision, radar processing, speech recognition, and text classification. It works by classifying input data into objects or classes based on key features, using either supervised or unsupervised classification.

Unsupervised Learning
Unsupervised neural networks are trained by letting the neural network continually adjust itself to new inputs. They are used to draw inferences from data sets consisting of input data without labeled responses. You can use them to discover natural distributions, categories, and category relationships within data.

Clustering
Clustering is an unsupervised learning approach in which neural networks can be used for exploratory data analysis to find hidden patterns or groupings in data. This process involves grouping data by similarity. Applications for cluster analysis include gene sequence analysis, market research, and object recognition [10].

Using CNNs for deep learning has become increasingly popular due to three important factors:

1. CNNs eliminate the need for manual feature extraction the features are learned directly by the CNN.
2. CNNs produce state of the art recognition results.
3. CNNs can be retrained for new recognition tasks, enabling you to build on pre-existing networks.

4.3 Layers In Network

1. A convolutional neural network can have tens or hundreds of layers that each learn to detect different features of an image [5].
2. Filters are applied to each training image at different resolutions, and the output of each convolved image is used as the input to the next layer.
3. The filters can start as very simple features, such as brightness and edges, and increase in complexity to features that uniquely define the object.
4. CNN perform feature identification and classification of images, text, sound, and video.
5. Like other neural networks, a CNN is composed of an input layer, an output layer, and many hidden layers in between.

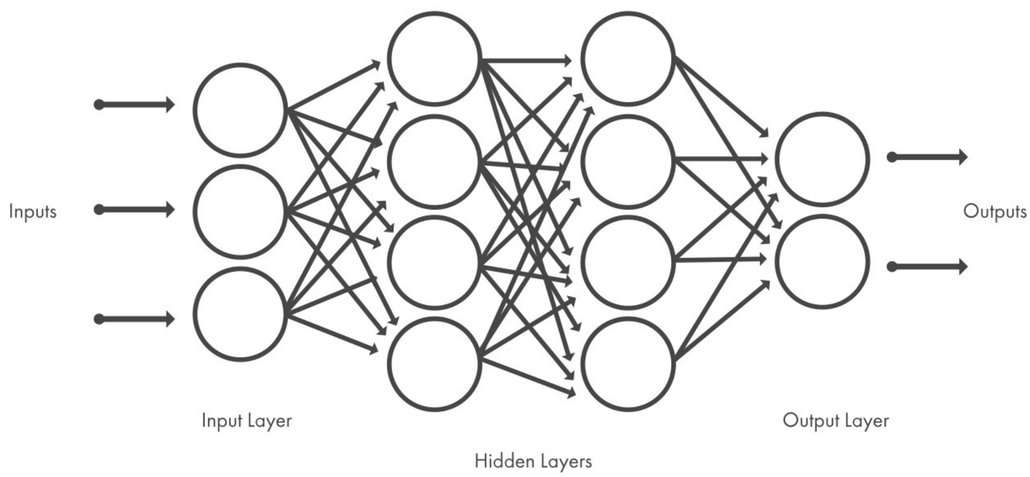

Figure 4.3: Hidden Layers in CNN

These layers perform operations that alter the data with the intent of learning features specific to the data. Three of the most common layers are:

1. Convolution

2. Activation or ReLU

3. Pooling

Convolution

Sentences the input images through a set of convolutional filters, each of which activates certain features from the images.

Rectified linear unit (ReLU)

It allows for faster and more effective training by mapping negative values to zero and maintaining positive values. This is sometimes referred to as activation, because only the activated features are carried forward into the next layer.

Pooling

It simplifies the output by performing nonlinear downsampling, reducing the number of parameters that the network needs to learn. These operations are repeated over tens or hundreds of layers, with each layer learning to identify different features.

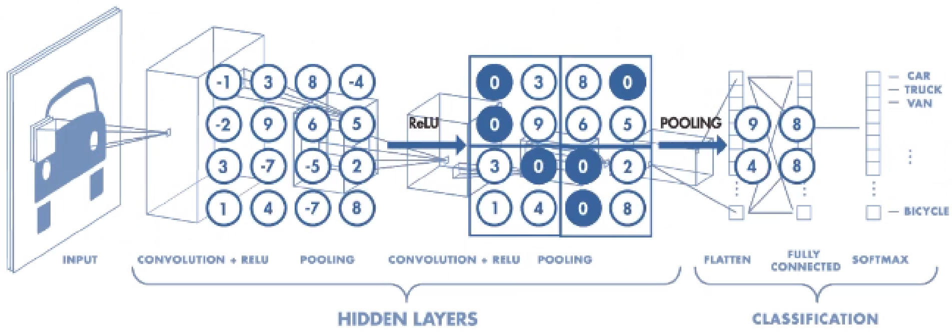

Figure 4.4: Internal Layers

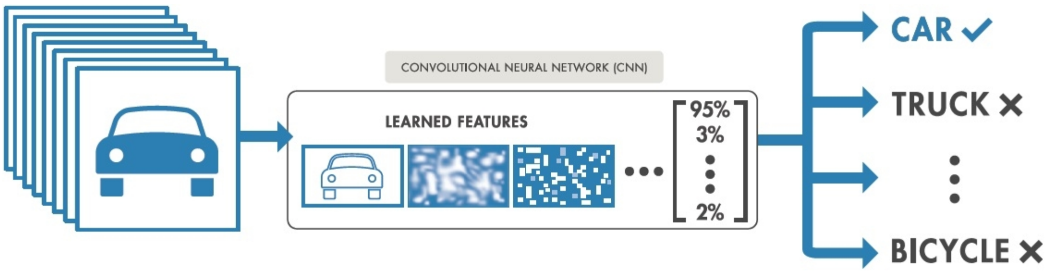

Figure 4.5: Constrained View

4.4 Preprocessing, Postprocessing, And Improving The Network

4.4.1 Pre-Processing

Updating the network inputs and targets improves the efficiency of shallow neural network training. Pre-Processing of an image means "preparation" of the sample/image to introduce it to an algorithm for specified task such as tracking targets , recognition, feature extraction, etc . It involves the size adjusting of the considered image, luminance normalization, statistical normalization , filtering noise with specified filter (Gaussian kernel, median), conversion to certain class.

4.4.2 Post-Processing

It enables detailed analysis of network performance. MATLAB provide tools to help:

1. Reduce the dimensions of input vectors using principal component analysis
2. Perform regression analysis between the network response and the corresponding targets
3. Scale inputs and targets so they fall in the range [-1,1]
4. Normalize the mean and standard deviation of the training data set

4.4.3 Improving The Networks Ability

It helps prevent overfitting, a common problem in neural network design [6]. Overfitting occurs when a network has memorized the training set but has not learned to generalize to new inputs. Overfitting produces a relatively small error on the training set but a much larger error when new data is presented to the network. Two solutions to improve overfitting include:

1. Regularization modifies the networks performance function. By including the sizes of the weights and biases, regularization produces a network that performs well with the training data and exhibits smoother behavior when presented with new data.
2. Early stopping uses two different data sets: the training set, to update the weights and biases, and the validation set, to stop training when the network begins to overfit the data.

4.5 Registration And Classification

After learning features in many layers, the architecture of a CNN shifts to classification. The next-to-last layer is a fully connected layer that outputs a vector of K dimensions where K is the number of classes that the network will be able to predict. This vector contains the probabilities for each class of any image being classified. The final layer of the CNN architecture uses a classification layer such as softmax to provide the classification output.

4.5.1 Network Structures

1. **Image Input Layer**
   An imageInputLayer is where you specify the image size, which, in this case, is 256-by-256-by-1. These numbers correspond to the height, width, and the channel size. The digit data consists of grayscale images, so the channel size is 1. For a color image, the channel size is 3, corresponding to the RGB values. You do not need to shuffle the data because trained network, by default, shuffles the data at the beginning of training. Trained network can also automatically shuffle the data at the beginning of every epoch during training.

2. **Convolutional Layer**
   In the convolutional layer, the first argument is filterSize, which is the height and width of the filters the training function uses while scanning along the images. You can specify different sizes for the height and width of the filter. This parameter determines the number of feature maps. Use the 'Padding' name-value pair to add padding to the input feature map. For a convolutional layer with a default stride of 1, 'same' padding ensures that the spatial output size is the same as the input size.

3. **Batch Normalization Layer**
   Batch normalization layers normalize the activations and gradients propagating through a network, making network training an easier optimization problem. Use batch normalization layers between convolutional layers and nonlinearities, such as ReLU layers, to speed up network training and reduce the sensitivity to network initialization. Use batchNormalizationLayer to create a batch normalization layer.

4. **ReLU Layer**
   The batch normalization layer is followed by a nonlinear activation function. The most common activation function is the rectified linear unit (ReLU). Use reluLayer to create a ReLU layer.

5. **Max Pooling Layer** Convolutional layers (with activation functions) are sometimes followed by a down-sampling operation that reduces the spatial size of the feature map and removes redundant spatial information. Down-sampling makes it possible to increase the number of filters in deeper convolutional layers without increasing the required amount of computation per layer. One way of down-sampling is using a max pooling, which you create using maxPooling2dLayer. The max pooling layer returns the maximum values of rectangular regions of inputs, specified by the first argument, poolSize.

6. **Fully Connected Layer**
   The convolutional and down-sampling layers are followed by one or more fully connected layers. As its name suggests, a fully connected layer is a layer in which the neurons connect to all the neurons in the preceding layer. This layer combines all the features learned by the previous layers across the image to identify the larger patterns. The last fully connected layer combines the features to classify the images. Therefore, the OutputSize parameter in the last fully connected layer is equal to the number of classes in the target data.

7. **Softmax Layer**
   The softmax activation function normalizes the output of the fully connected layer. The output of the softmax layer consists of positive numbers that sum to one, which can then be used as classification probabilities by the classification layer. Create a softmax layer using the softmaxLayer function after the last fully connected layer.

8. **Classification Layer**
   The final layer is the classification layer. This layer uses the probabilities returned by the softmax activation function for each input to assign the input to one of the mutually exclusive classes and compute the loss. To create a classification layer, use classificationLayer.

4.5.2 Specify Training Options

After defining the network structure, specify the training options. Train the network using stochastic gradient descent with momentum (SGDM) with an initial learning rate of 0.01. Set the maximum number of epochs to 50. An epoch is a full training cycle on the entire training data set. Monitor the network accuracy during training by specifying validation data and validation frequency. Shuffle the data every epoch. The software trains the network on the training data and calculates the accuracy on the validation data at regular intervals during training. The validation data is not used to update the network weights. Turn on the training progress plot, and turn off the command window output[3].

4.5.3 Train Network Using Training Data

Train the network using the architecture defined by layers, the training data, and the training options. By default, trainNetwork uses a GPU if one is available. Otherwise, it uses a CPU. You can also specify the execution environment by using the 'ExecutionEnvironment' name-value pair argument of trainingOptions. The training progress plot shows the mini-batch loss and accuracy and the validation loss and accuracy. The loss is the cross-entropy loss. The accuracy is the percentage of images that the network classifies correctly.

4.5.4 Neurons

1. The neurons in each layer of a ConvNet are arranged in a 2-D manner, transforming a 2-D input to a 2-D output.

2. The neurons in the first convolutional layer connect to the regions of these images and transform them into a 2-D output.

3. The hidden units (neurons) in each layer learn nonlinear combinations of the original inputs, which is called feature extraction.

4. These learned features, also known as activations, from one layer become the inputs for the next layer.

5. Finally, the learned features become the inputs to the classifier or the regression function at the end of the network.

6. The architecture of a ConvNet can vary depending on the types and numbers of layers included. The types and number of layers included depends on the particular application or data.

7. A smaller network with only one or two convolutional layers might be sufficient to learn a small number of gray scale image data. On the other hand, for more complex data with millions of colored images, we may need a more complicated network with multiple convolutional and fully connected layers.

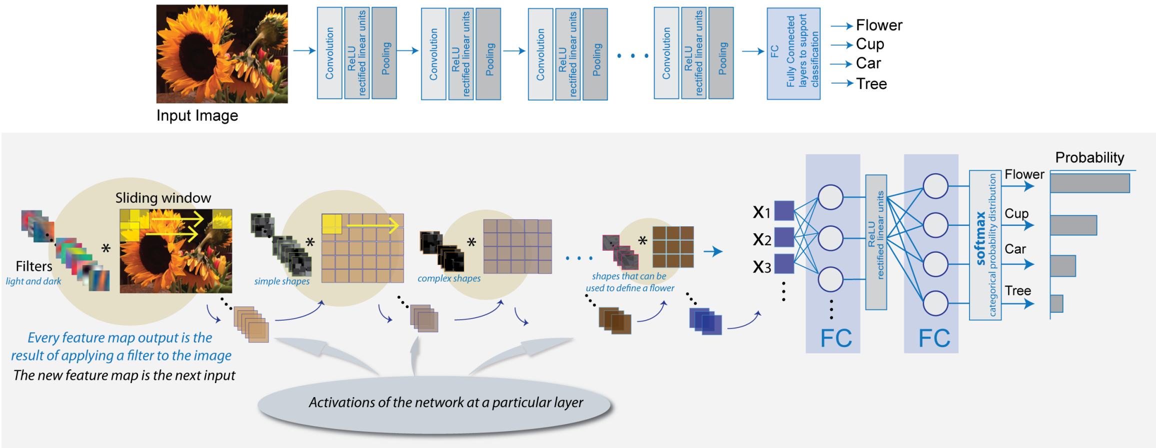

Figure 4.6: Deep Learning Architecture

4.6 Typical Workflow for Designing Neural Networks

Each neural network application is unique, but developing the network typically follows these steps:

1. Access and prepare data
2. Create the neural network
3. Configure the networks inputs and outputs
4. Tune the network parameters (the weights and biases) to optimize performance
5. Train the network
6. Validate the networks results
7. Integrate the network into a production system

4.6.1 Insight Into Different Optimisers Used

1. **Stochastic Gradient Descent With Momentum**
   Gradient descent is a First Order Optimization Method. It only takes the first order derivatives of the loss function into account and not the higher ones. What this basically means it has no clue about the curvature of the loss function. It can tell whether the loss is declining and how fast, but cannot differentiate between whether the curve is a plane, curving upwards or curving downwards.

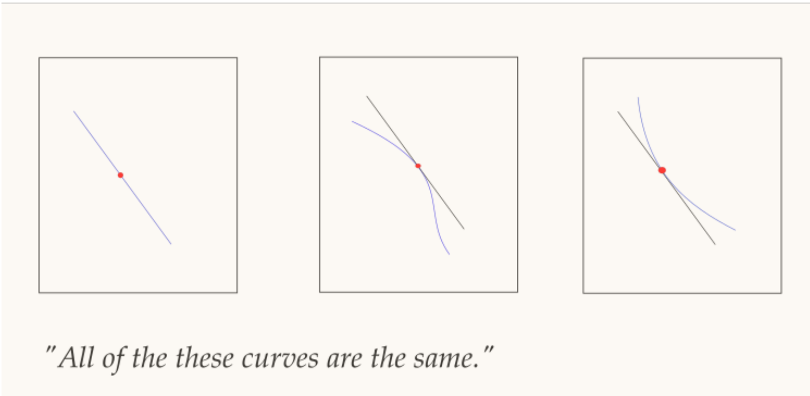

Figure 4.7: SGDM Curves

2. **RMSProp or Root Mean Square Propogation**
   It has an interesting history. It was devised by the legendary Geoffrey Hinton. RMSProp also tries to dampen the oscillations, but in a different way than momentum. RMS prop also takes away the need to adjust learning rate, and does it automatically. More so, RMSProp choses a different learning rate for each parameter. In RMS prop, each update is done according to the equations described below. This update is done separately for each parameter.

$$v_t = \rho v_t - 1 + (1 - \rho) * g_t^2$$

$$\Delta w_t = \frac{-\eta}{\sqrt{v_t + \epsilon}} * g_t$$

$$w_t + 1 = w_t + \Delta w_t$$

   a) In the first equation, we compute an exponential average of the square of the gradient.

   b) Then in the second equation, we decided our step size.

   c) The third equation is just the update step. The hyperparameter p is generally chosen to be 0.9, but you might have to tune it.

3. **Adam or Adaptive Moment Optimization**

   This algorithms combines the features of both Momentum and RMSProp. Here, we compute the exponential average of the gradient as well as the squares of the gradient for each parameters. To decide our learning step, we multiply our learning rate by average of the gradient (as was the case with momentum) and divide it by the root mean square of the exponential average of square of gradients (as was the case with momentum). Then, we add the update. Out of the above three, you may find momentum to be the most prevalent, despite Adam looking the most promising on paper. Empirical results have shown the all these algorithms can converge to different optimal local minima given the same loss. However, SGD with momentum seems to find more flatter minima than Adam, while adaptive methods tend to converge quickly towards sharper minima. Flatter minima generalize better than sharper ones [7]. Along with choosing better optimization methods, considerable research is being put in coming up with architectures that produce smoother loss functions to start with. Batch Normalization and Residual Connections are a part of that effort.

4.7 Working Procedure

4.7.1 Preparation of Datasets

1. Firstly the collected datasets are divided into two folders namely registered and unregistered.
2. This is mainly for classification of brain with tumor and without tumor.
3. The remaining datasets are combined ,i.e both CT and MRI images are then divided into 20 sub folders.
4. Each sub-folders will have images rotated beginning with a initial rotation of 2.
5. This is mainly for angle classification.
6. Once the datasets are prepared, next is to build a convolutional neural network.
7. Different optimizers are used for training.

4.7.2 Setting Training Parameters

1. The neural network designed for tumor classification includes total of 3 layers, the optimiser used is 'SGDM'.
2. While the neural network designed for angle classification includes total of 4 layers, the optimiser used is 'ADAM'.
3. The epochs and filter size are set in order to get the maximum accuracy.
4. The training and validation data are chosen randomly with a 70:30 ratio.
5. All the remaining parameters like learning rate, mini batch size and validation frequency are set to default values.

4.7.3 Training and Classification

1. First for angle classification,once the training is done save the trained matrix as trained.mat.
2. Then for registration load back the saved matrix and classify with the input image.
3. Based on the features extracted by the network the classifier yields a categorical value.
4. This categorical value is converted to angle with a for formula **'angle=categorical*2'**
5. Registration is performed by rotating the input image in reverse direction of angle obtained.
6. Finally for tumor classification,load the trained matrix trained1.mat (obtained by training registered and unregistered image)
7. Then perform classification of registered image with trained1.mat
8. The classifier yields a string value whether positive if tumor present or negative if tumor is absent.

4.8 Registration Results

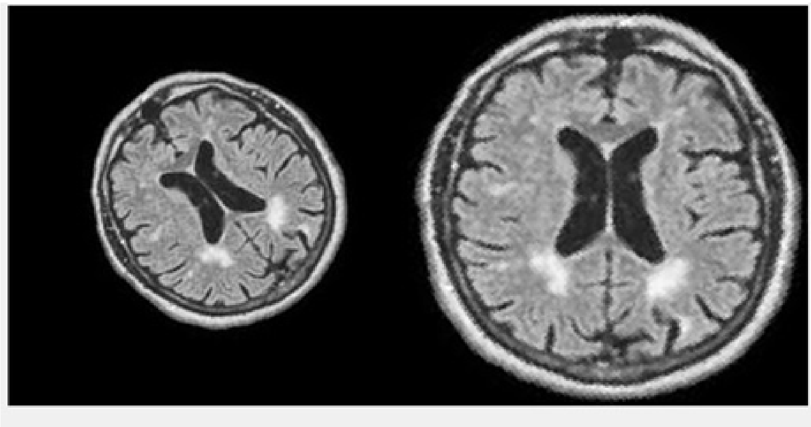

Figure 4.8: Registered Image With Tumor; Registration method is angle based registration

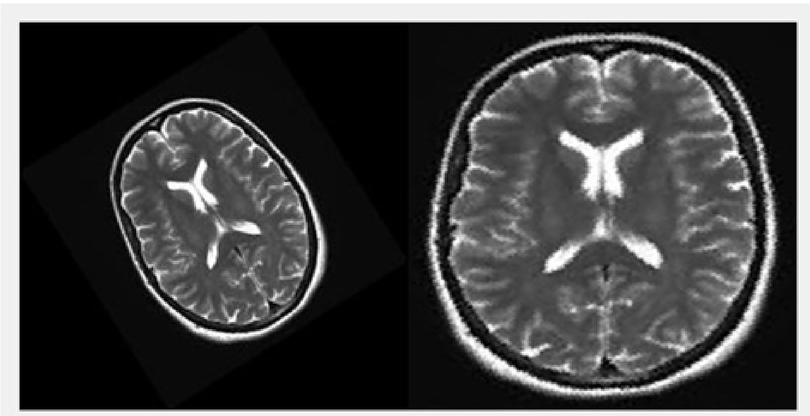

Figure 4.9: Registered Image Without Tumor; Registration method is angle based registration

4.9 Results

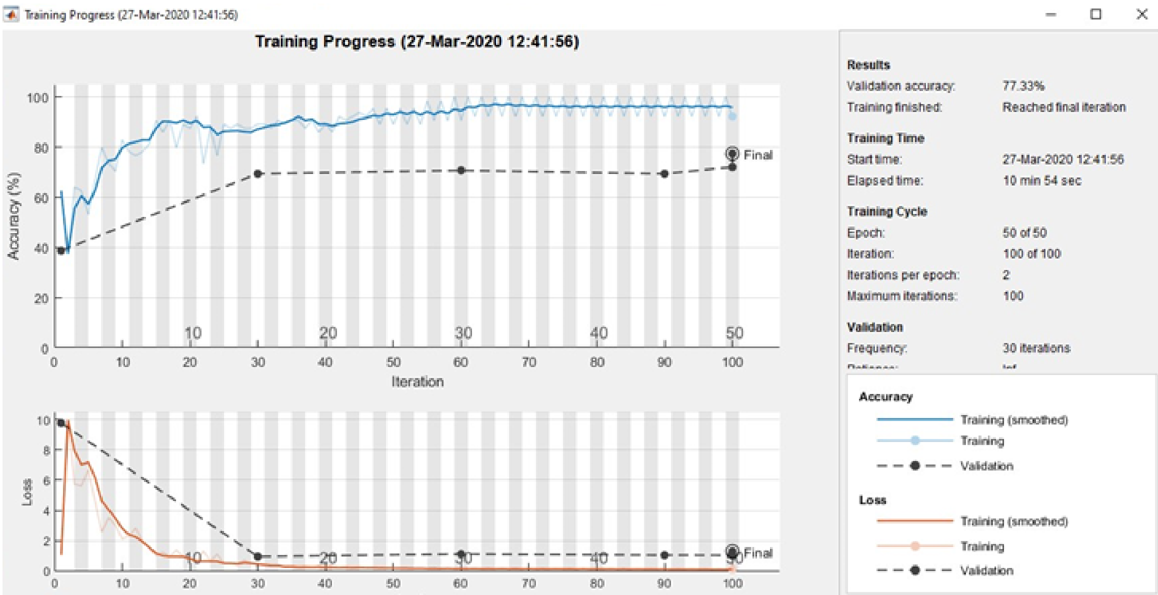

Figure 4.10: Accuracy Plot-Training Angle Class; Overall Accuracy obtained is 78%; Total iterations are 100, with 2 iteration per epoch

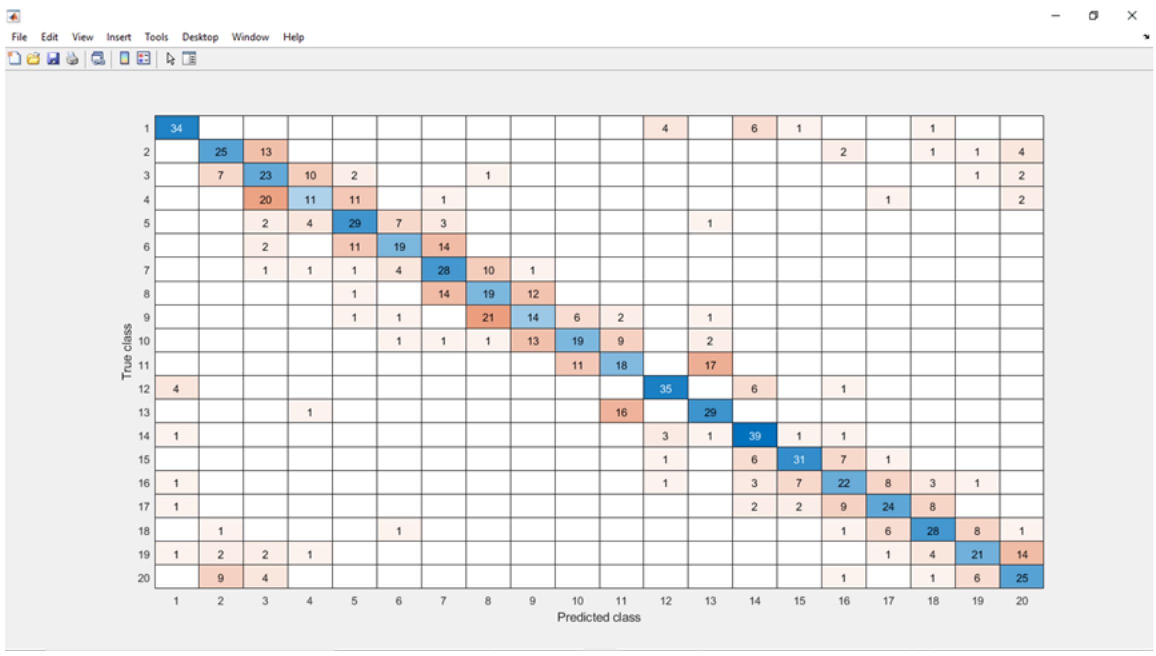

Figure 4.11: Confusion Chart For Angle Classification; Total output classes obtained were 20 , the diagonal elements highlighted in blue are the number of images correctly classifed

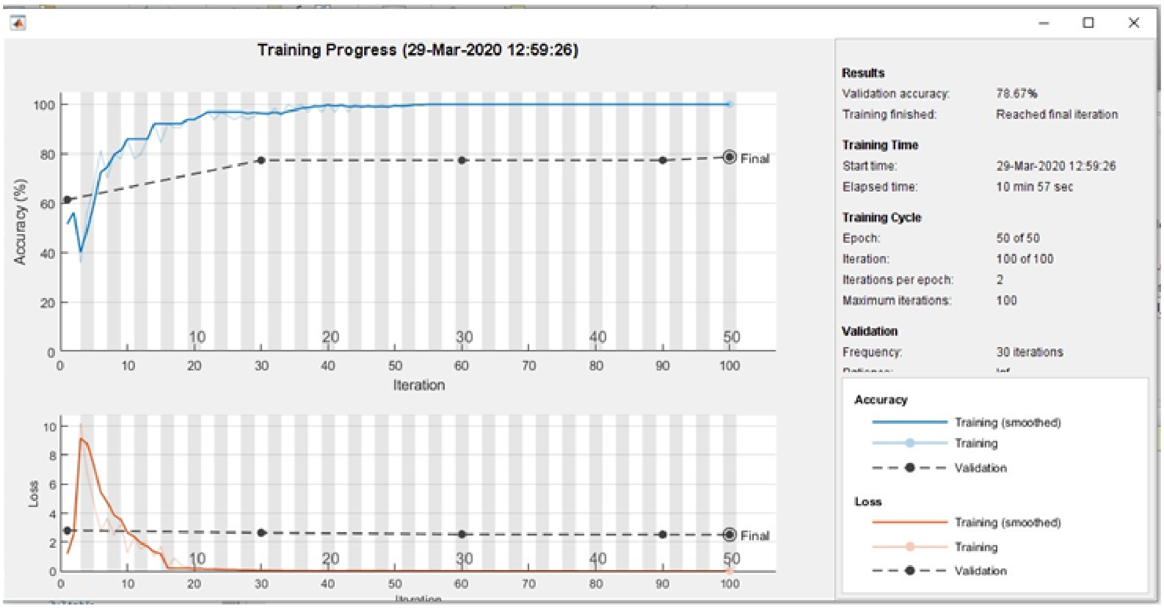

Figure 4.12: Accuracy Plot-Training Tumor Class;Overall Accuracy obtained is 79%; Total iterations are 100, with 2 iteration per epoch

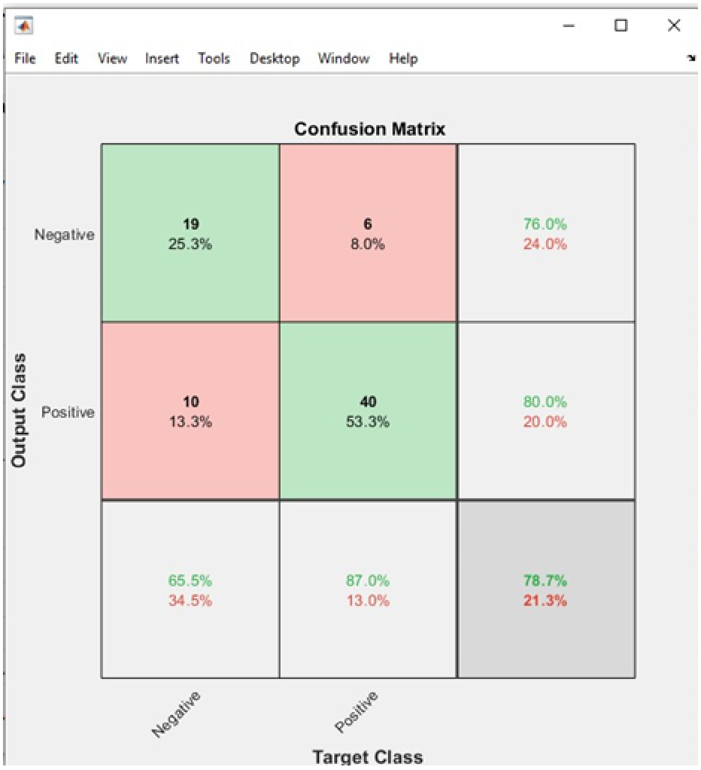

Figure 4.13: Confusion Matrix For Tumor Classification; Total output classes obtained were 2 , the diagonal elements shows the number of images correctly classifed

Chapter 5

DWT-PCA Fusion

5.1 Introduction

Combining fundamental and functional medical images to provide much more useful information through image fusion. To get a high-resolution image with as much details as possible for the correct diagnosis is the main objective of medical imaging. CT gives best information about denser tissue and MRI provides better information on soft tissue.Both the techniques give special refined characteristics of the organ to be imaged. So, it is best that the fusion of MRI and CT images of the same organ would result in an integrated image with detail information . Image fusion is a device to integrate multi-modal medical images by using image processing techniques. Precisely it aims at the integration of disparate and complementary data in order to enhance the information visible in the images.
It also upturns the reliability of interpretation, consequently leading to more accurate data and increased efficiency. Besides, it has been stated that fused data gives, robust operational performance such as increased confidence, reduced ambiguity, improved reliability and improved classification . Image Fusion are applied in every field where images should be analyzed. For example, medical image analysis, microscopic imaging, analysis of images from satellite, remote sensing Application, computer vision, robotics etc . Different techniques are used for image fusion through the evolution. On this many approaches are used. They are of Spatial-domain like IHS, PCA, averaging, brovey transformation, etc and other type is Transformation-domain i.e is like pyramid, wavelet, curvelet transformation, etc.
The disadvantage of spatial domain approaches is that they create spatial distortion in the fused image. Spectral distortion becomes a negative factor while we go for further processing such as classification problem . Spatial distortion can be very well handled by frequency domain approaches on image fusion. The multi resolution analysis has become a very useful tool for analyzing remote sensing images. The discrete wavelet transform has become a very useful tool for fusion. The method uses pixel level and a data set of two modalities CT/MRI images to fuse to get a relevant and redundant information by using the DWT & PCA techniques. And then compare the two methods with analytical values and qualitative matrices like MSE, PSNR.

5.2 Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is a mathematical tool for hierarchically decomposing an image. With strong spatial support, the DWT provides a compact representation of a signals frequency component [12]. DWT decomposes a image into frequency sub-band at different scale from which it can be perfectly reconstructed. The signal into high and low frequency parts is split by the DWT. The low frequency part contains coarse information of signal whereas high frequency part contains information about the edge components. Two dimensional Discrete Wavelet Transform implements image fusion. The resolution of an image, which is a evaluate amount of detail information in the image, is changed by filtering operations of wavelet transform. And the scale is changed by sampling. The DWT analyses the image at different frequency bands with different resolutions by decomposing the image into approximation and detail coefficients.

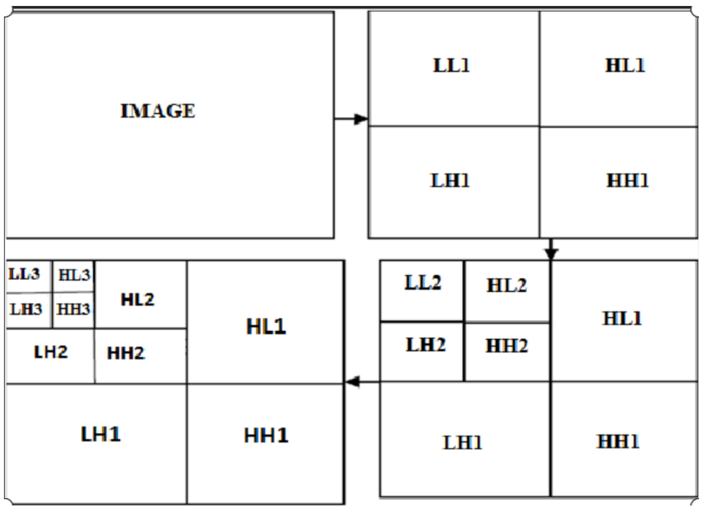

Figure 5.1: Image Decomposition using 2D DWT

5.3 One Level Transform

The DWT of a signal is calculated by passing it through a series of filters [13]. First the samples are passed through a low pass Filter with Impulse response resulting in a convolution of the two:

$$y[n] = (x + g)[n] = \sum_{k=\infty}^{\infty} x[k]g[n-k]$$

The signal is also decomposed simultaneously using a high pass filter. The outputs give the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter

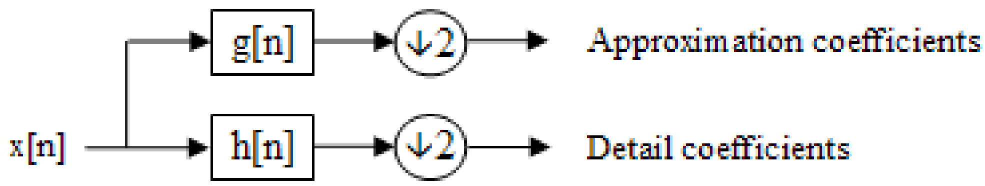

Figure 5.2: Block diagram of filter analysis

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquists rule. The filter output of the low-pass filter in the diagram above is then sub-sampled by 2 and further processed by passing it again through a new low- pass filter and a high- pass filter with half the cut-off frequency of the previous one,i.e.:

$$y_l[n] = \sum_{k=\infty}^{\infty} x[k]g[2n-k]$$

$$y_h[n] = \sum_{k=\infty}^{\infty} x[k]h[2n-k]$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input, so the frequency resolution has been doubled. With the sub-sampling operator the above summation can be written more concisely

Ylow=(x*g)

Yhigh=(x*h)

However computing a complete convolution with subsequent down sampling would waste computation time. The Lifting Scheme is an optimization where these two computations are interleaved. For example a signal with 32 samples, frequency range 0 to and 3 levels of decomposition, 4 output scales are produced [14].

Table 5.1: Table showing different levels and corresponding frequency narrowing

Level	Frequencies	Sample
3	0 to f/8	4
3	f/8 to f/4	4
2	f/4 to f/2	8
1	f/2 to f	16

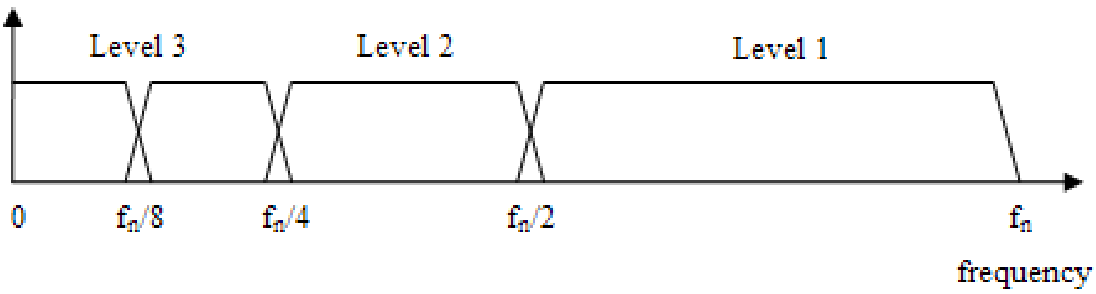

Figure 5.3: Frequency domain representation of DWT

5.4 Cascading and filter banks

This decomposition is repeated to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters and then down-sampled. This is represented as a binary tree with nodes representing a sub-space with a different time-frequency localization. The tree is known as a filter bank.

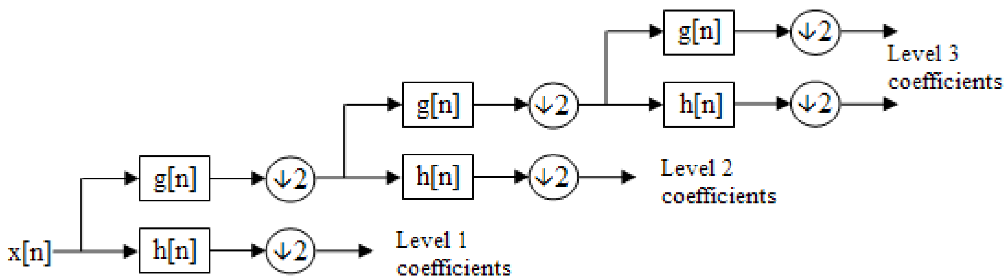

Figure 5.4: A3 level Filter bank

At each level in the above Figure 5.4 the signal is decomposed into low and high frequencies. Due to the decomposition process the input signal must be a multiple of where is the number of levels. Wavelet separately filters and down samples the 2-D data (image) in the vertical and horizontal directions (separable filter bank). The input (source) image is I (x.y) filtered by low pass filter L and high pass filter H in horizontal direction and then down sampled by a factor of two (keeping the alternative sample) to create the coefficient matrices IL (x,y) and I H(x,y) .The coefficient matrices IL (x,y) and I H(x,y) are both low pass and high pass filtered in vertical direction and down sampled by a factor of two to create sub bands (sub images) ILL (x,y) , ILH(x,y), IHL (x,y) and IHH(x,y)

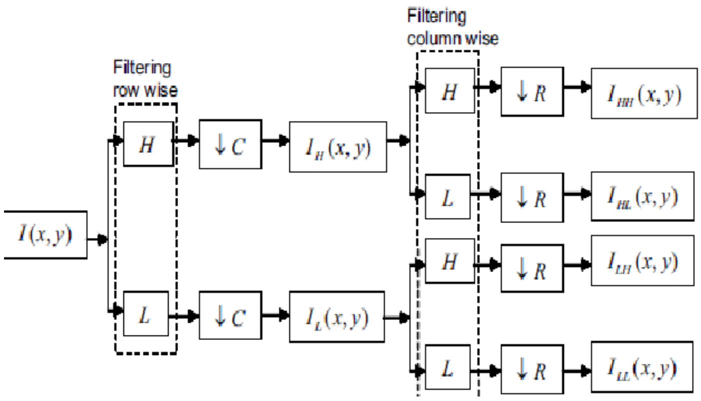

Figure 5.5: One level of 2-D image decomposition

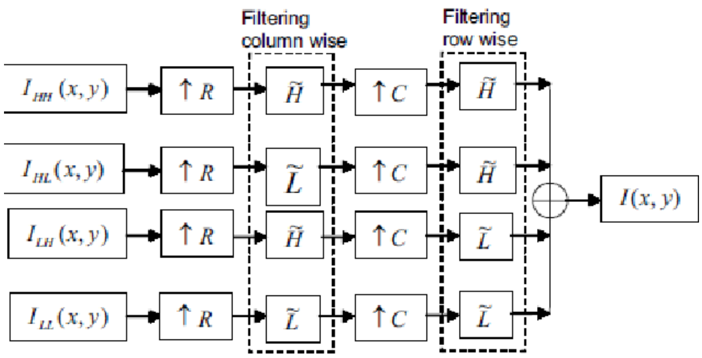

Figure 5.6: One level of 2-D image reconstruction

The ILL (x,y), comprises the average image information corresponding to low frequency band of multi scale decomposition. It could be measured as smoothed and sub sampled version of the source image I . It represents the approximation of source image. I (x,y), ILH (x,y), IHL (x,y), and IHH (x,y), are detailed sub images which contain directional (horizontal, vertical and diagonal) information of the source image I (x,y) due to spatial orientation. Multi-resolution could be achieved by recursively applying the same algorithm to low pass coefficients from the previous decomposition. Inverse 2-D wavelet transform is used to reconstruct the image I (x,y), from sub images ILL (x,y), ILH (x,y), IHL (x,y), and IHH (x,y) as shown in Figure.5.9. This involves column up sampling (inserting zeros between samples) and filtering using low pass L and high pass filter H for each sub images. The image I (x,y) would be constructed by row up sampling and filtering with low pass filter L and high pass filter H of the resulting image and summation of all matrices.

5.5 Principle Component Analysis

The PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables. It computes a compact and optimal description of the data set. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. PCA is also a linear transformation and is widely used in data compression and pattern matching.

5.6 PCA Algorithm

Let the source images (to be fused) of size m x n matrix, the steps for PCA are:

1. Organize the data into column matrix. The resulting matrix Z is of dimension 2 x n.
2. Calculate the empirical mean along each column. Assign The empirical mean matrix M of 1 x 2.
3. Subtract the empirical mean vector M from each column of the data matrix Z. The resulting matrix X is of dimension 2 x n i.e
4. Find the co variance matrix C of X i.e.C=XXT mean of expectation = cov(X)
5. Compute the eigen vectors V and eigenvalue D of C and sort them by decreasing eigenvalue. Both V and D are of dimension 2 x 2.
6. Consider the first column of V which corresponds to larger eigenvalue to compute P1 and P2 as:

$$P_1 = \frac{V(1)}{\sum V}$$

$$P_2 = \frac{V(2)}{\sum V}$$

5.7 Image Fusion by PCA

The information flow diagram of PCA-based image fusion algorithm is shown in Figure. 5.7 . The input images (images to be fused) I1 (x,y) and I 2(x,y) are arranged in two column vectors and their empirical means are subtracted. The resulting vector has a dimension of n x 2, where n is length of the each image vector. The eigen vector and eigenvalues for this resulting vector are computed and the eigen vectors corresponding to the larger eigenvalue achieved. The normalized components P1 and P2 (i.e., P1 + P2 = 1) are computed from the obtained eigen vector. The fused image is: If (x,y) = P1I1 (x,y) + P2I2 (x,y).

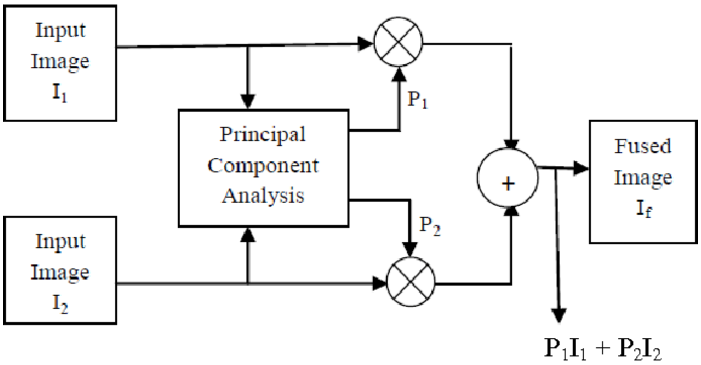

Figure 5.7: PCA Fusion block diagram

5.8 Proposed Method

In this project , image fusion of two modality images i.e. CT and MRI is performed. Consider image I1 as CT and image I2 as MRI. The following steps are the proposed methods, as shown in Figure 5.8.

1. The images to be fused must be registered to assure the corresponding pixels are aligned together i.e. registered image I1 and I2.

2. This method is considered as the most efficient in terms of computation time since Haar wavelet is used. By applying DWT (haar), the reg image I1 and I2 are decomposed i.e. LL1, LH1, HL1, HH1= DWT reg image I1 and LL2, LH2,

HL2, HH2= DWT reg image I2 to obtain the coefficients and the reg images are subjected to 3-level decomposition

3. The resulting coefficients are evaluated using PCA for both dimension reduction as well as to obtain best coefficients for fusion. Now, using each coefficients of reg image I1 and I2 and applying PCA by taking respective coefficients

4. The fusion rule involves multiplication of each principle component with each decimated wavelet coefficient adding them to obtained fused image

5. The fused image is constructed by performing the IDWT (Haar) based on the combined transform coefficients from previous step

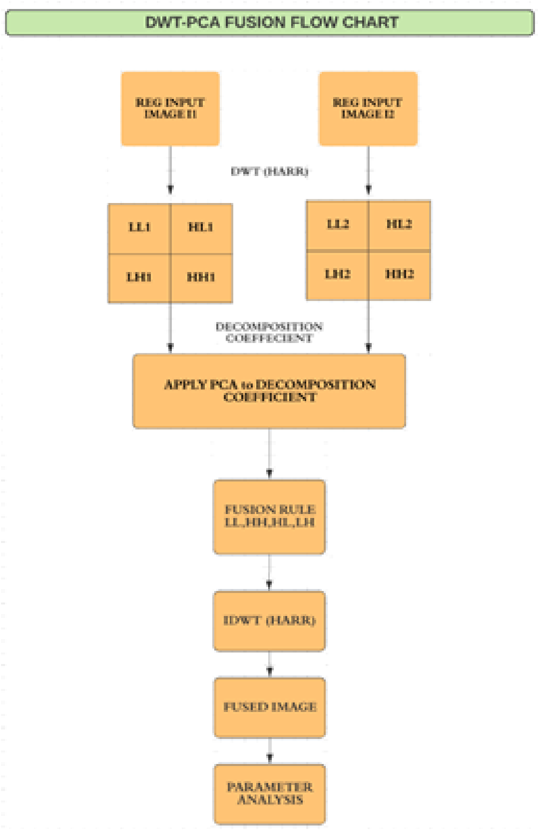

Figure 5.8: Flow chart DWT-PCA Fusion.

5.9 Performance Evaluation

The two modality CT and MRI images are fused by proposed method i.e integrating of DWT and PCA methods.The fused image is analyzed with MSE, PSNR, Entropy, the values of these over proposed method gives better results. In the MRI image, the inner contour is missing but it provides better information on soft tissue. In the CT image, it provides the best information on denser tissue with less distortion, but it misses the soft tissue information.

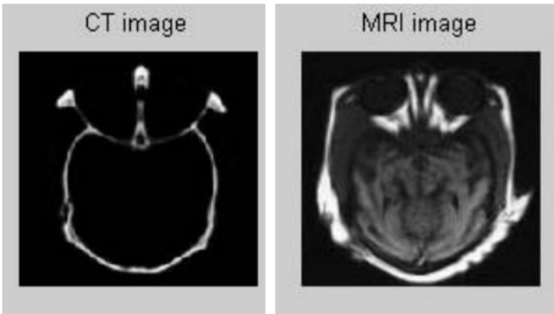

Figure 5.9: Input image1 and Input image2, CT and MRI

Fusion.png Fusion.pdf Fusion.jpg Fusion.mps Fusion.jpeg Fusion.jbig2 Fusion.jb2 Fusion.PNG Fusion.PDF Fusion.JPG Fusion.JPEG Fusion.JBIG2 Fusion.JB2

Figure 5.10: Fusion results of various methods

Fused images by (a) Normal Min (b) Bi-orthogonal (c) PCA method (d) DWT(Haar) (e) 3- level of decomposition (f) the proposed method DWT-PCA and Analog BF532 support image fusion. The fusion of CT and MRI of two modality images improves the view of the images and adds information of both anatomical and physiological information in one image for further segmentation to accurately detect brain tumor region. The Wavelet transforms is the best technique for the image fusion which provides a high quality spectral content. But a good fused image has both quality so the combination of DWT & spatial domain fusion method (like PCA) fusion algorithm improves the performance as compared to use of individual DWT and PCA algorithm.

5.9.1 Results Of Fusion

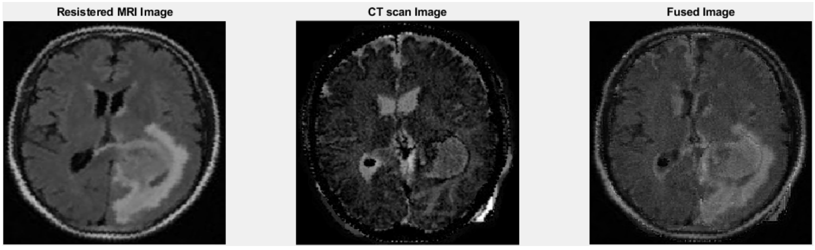

Figure 5.11: Example-1:Image Fusion;The MRI and CT images are registered first and then the fusion takes place.

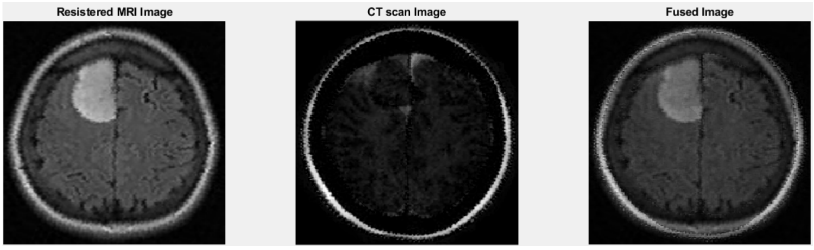

Figure 5.12: Example-2:Image Fusion; Fused image gives more insight into the corners and edges while preserving the image quality.

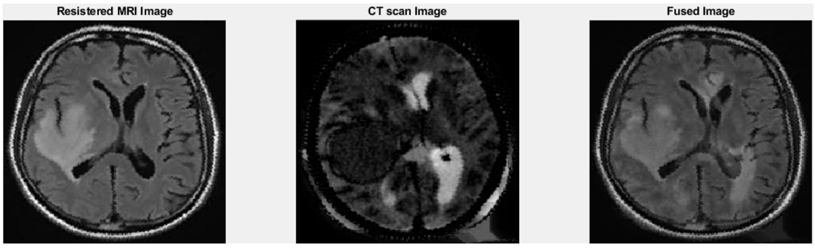

Figure 5.13: Example-3:Image Fusion; Fused image has less noise,indicating the fusion method used was good.

Chapter 6

Segmentation and Detection

6.1 Introduction

Brain tumor segmentation is the process of separating the tumor from normal brain tissues. It provides useful information for diagnosis and treatment planning. Brain tumor segmentation is an important task in medical image processing. Early diagnosis of brain tumors plays an important role in improving treatment possibilities and increases the survival rate of the patients [15]. To diagnose human brain structure safe imaging techniques are used throughout the world. CT, MRI, and multimodal imaging techniques such as MRI/CT are various imaging techniques that provide information from a variety of excitation sequences about brain tissues.
The segmentation is the method of dividing an image into various regions, such that the pixels within the region have similar characteristics. In the specific case of MRI brain image, separation of different tumor tissues from normal tissues is labeled as segmentation process. The manual segmentation of tumor from the images involves huge processing time and may produce the inaccurate results. In order to help doctors for diagnosis and treatment of tumour and to help researcher for studying the brain activities, the research in automatic segmentation techniques of brain tumour is gaining more importance. The technique which is used for segmentation is Morphological-Based Method. Morphology operation is based on the morphology of features of the image.
Automatic segmentation of brain tumour is the process of separating abnormal tissues from normal tissues, such as white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). The process of segmentation is still challenging due to the diversity of shape, location, and size of the tumour segmentation. The metabolic process, psychological process, and detailed information of the images, are obtained using Computer Tomography (CT) image and Magnetic Resonance Image (MRI). Multimodal imaging techniques (such as CT and MRI) that combine the information from many imaging techniques contribute more for accurate brain tumour segmentation [16].

6.1.1 Various Techniques for Segmentation

The different techniques for segmentation are :

1. Thresholding method
2. Edgebased Method
3. Background method
4. Region growing method
5. Watershed Algorithm
6. Morphological-Based Method
7. Genetic Algorithm
8. Fuzzy Clustering.

Morpological Based Method

Morphology operation is based on the morphology of features of the image. It is mainly used for extraction of information from the image based on the representation of the shape. Dilation and erosion are two basic operations . Dilation is used for dilating the size of the image. Images are shrunk by erosion. the proposed method is able to segment tumour even in low-intensity images. The method involves several steps to extract tumour from the image, which includes enhancement of image, resampling of image, color plane extraction, histogram application, an advanced morphological operation to extract tumour region. In the proposed method, morphological operations are mainly used as the filter to remove low-frequency pixels and boundary pixels. Area of tumour, length, and other parameters of the tumour are identified effectively for treatment and diagnosis of the tumour [17].

6.1.2 Steps involved in tumour segmentation

The different steps used are :

1. Acquire the input Brain MRI
2. convert the input MRI into gray scale image
3. In preprocessing stage, improve the image contrast by histogram eualisation
4. Compute morphological operation on registered image
5. Finally display the segmented tumor region.

6.1.3 Morpological Operation Using Matlab

In a morphological operation, each pixel in the image is adjusted based on the value of other pixels in its neighborhood. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image [18].

6.1.4 Results Of Segmentation

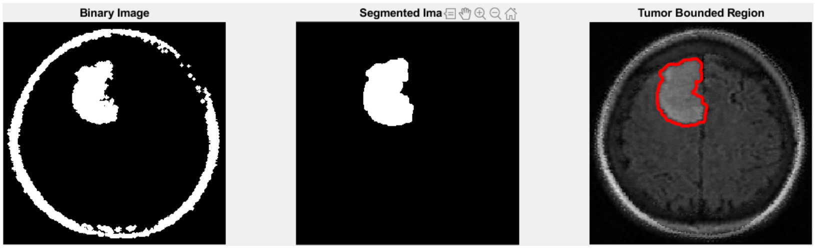

Figure 6.1: Ex 1:Segmented Image;The binary image and the segmented image can be found alongside with the tumor bounded region.

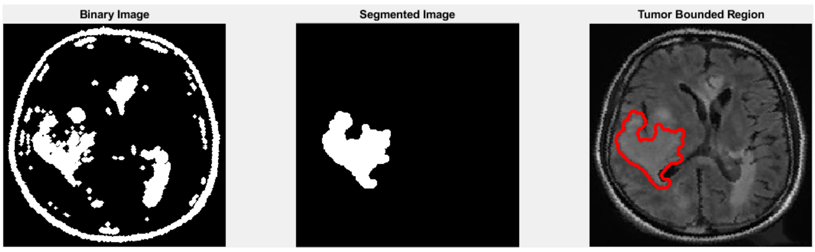

Figure 6.2: Ex 2:Segmented Image; Morphological operations are performed to compute the tumor region;BwBoundaries are used to extract the tumor region

6.1.5 Performance Parameters

1. **PSNR**-peak signal to noise ratio calculates the peak signal-to-noise ratio for the image A, with the image ref as the reference

2. **SSIM**-Structural similarity (SSIM) index for measuring image quality This MATLAB function computes the structural similarity (SSIM) index for grayscale image or volume A using ref as the reference image

3. **MSE**-mse is a network performance function. It measures the networks performance according to the mean of squared errors. This function has two optional parameters, which are associated with networks whose net.trainFcn is set to this function: 'regularization' can be set to any value between 0 and 1. The greater the regularization value, the more squared weights and biases are included in the performance calculation relative to errors. The default is 0, corresponding to no regularization.

   'normalization' can be set to 'none' (the default); 'standard', which normalizes errors between -2 and 2, corresponding to normalizing outputs and targets between -1 and 1; and 'percent', which normalizes errors between -1 and 1. This feature is useful for networks with multi-element outputs.
   It ensures that the relative accuracy of output elements with differing target value ranges are treated as equally important, instead of prioritizing the relative accuracy of the output element with the largest target value range.

Table 6.1: Parameters Calculated To Validate The Fused Images

Angle	MSE	PSNR	SSIM	ENTROPY	STD
4	233.971	35.254	0.9245	6.4654	67.3210
10	249.208	34.874	0.9389	6.4785	66.721
20	252.34	32.45	0.9393	6.423	66.75
24	247.62	32.096	0.9355	6.6428	66.5281
34	240.0471	31.454	0.9279	6.6214	75.712

Chapter 7

Conclusion And Future Scope

Image Registration has been evolving in the few years,and has gained much concern due to the importance of such field as a powerful guide for the experts in the medicinal area. In our project we have introduced a new technique i.e angle based registration.This basically is done with the help of Convolutional Neural Network, by assesing the trained parameters. The accuracy of both the networks were found to be around 70%-80%.Once registration is performed, the registered image is classified as to predict if it has tumor or if it's a normal image.If the classifier classifies it as positive i.e with tumor, this image is subjected to segmentation using Otsu's Thresholding Method and finally we highlight the tumor region using morphologiacal operation which is bwboundaries.If classifier classifies it as negative image, then image fusion of the registered MRI and CT image is done,using DWT+PCA fusion method.Combination of these methods has proved to be very efficient with fused image having high PSNR value, low RMES(Root Mean Square Error).By implementing fusion we were able to detect the minute tumors present in the images. Upon fusion we subject the fused image to classification again and if the prediction is negative we finally conclude the input image has no tumor,if prediction is positive we perform segmentation and highlight the tumor region.
Further the training accuracy can be improved by increasing the number of datasets for training, building a neural network with more layers with reduced learning rate.Angle registration can be improved by varying the angle upto two decimal places also.Classifier accuracy can also be increased by adding more images with tumor and non tumor.A four level DWT can be done for more accurate fusion of images.Different higher level wavelets can be used for obtaining the filters required for fusion,which may enhance the fused image.

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Appendix A

Otsu's Thresholding Method

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum. Simple example to demonstrate the algorithm using 6x6 image shown below.

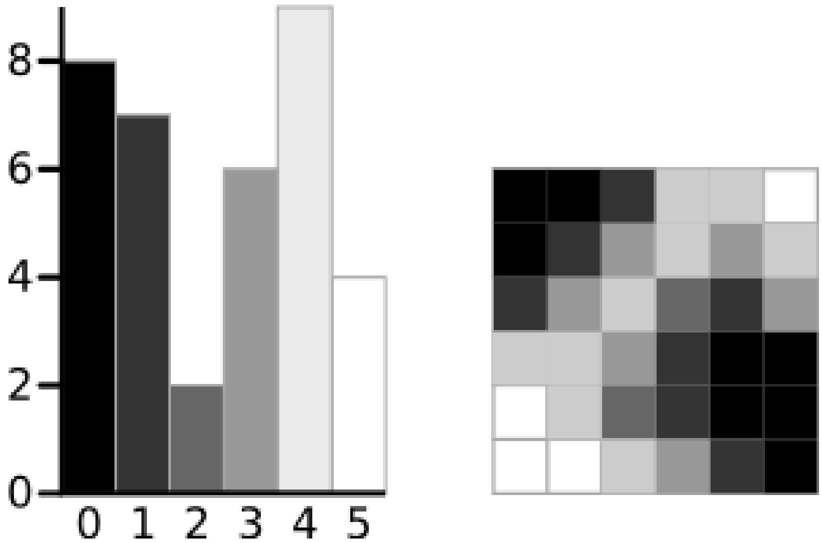


Figure A.1: Simple 6*6 gray scale image

The calculations for finding the foreground and background variances for a single threshold are below. In this case the threshold value is 3.

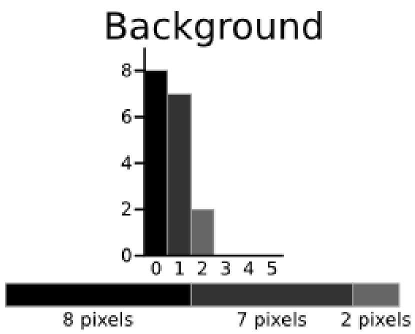


Figure A.2: Background Image

$$\text{Weight} \quad W_b = \frac{8+7+2}{36} = 0.4722$$

$$\text{Mean} \quad \mu_b = \frac{(0\times 8)+(1\times 7)+(2\times 2)}{17} = 0.6471$$

$$\begin{aligned}\text{Variance} \quad \sigma_b^2 &= \frac{((0-0.6471)^2\times 8)+((1-0.6471)^2\times 7)+((2-0.6471)^2\times 2)}{17}\\ &= \frac{(0.4187\times 8)+(0.1246\times 7)+(1.8304\times 2)}{17}\\ &= 0.4637\end{aligned}$$

Figure A.3: Background calculations

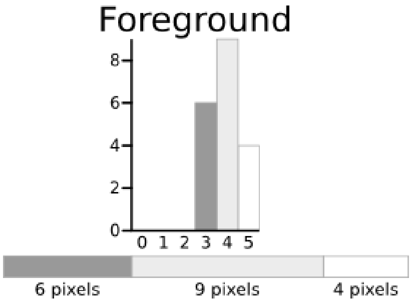


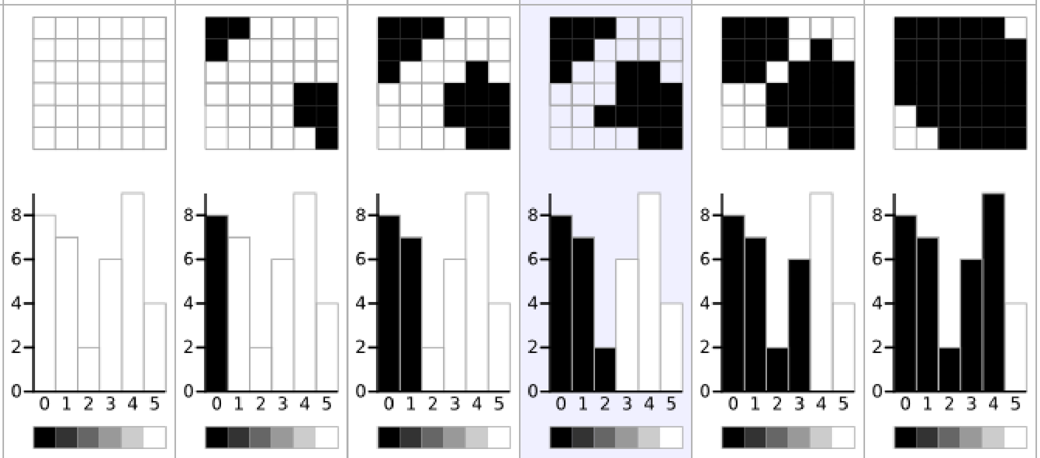
Figure A.4: Foreground Image

$$\text{Weight} \quad W_f = \frac{6+9+4}{36} = 0.5278$$

$$\text{Mean} \quad \mu_f = \frac{(3 \times 6) + (4 \times 9) + (5 \times 4)}{19} = 3.8947$$

$$\text{Variance} \quad \sigma_f^2 = \frac{((3-3.8947)^2 \times 6) + ((4-3.8947)^2 \times 9) + ((5-3.8947)^2 \times 4)}{19}$$
$$= \frac{(4.8033 \times 6) + (0.0997 \times 9) + (4.8864 \times 4)}{19}$$
$$= 0.5152$$

Figure A.5: Foreground calculation



Threshold	T=0	T=1	T=2	T=3	T=4	T=5
Weight, Background	$W_b = 0$	$W_b = 0.222$	$W_b = 0.4167$	$W_b = 0.4722$	$W_b = 0.6389$	$W_b = 0.8889$
Mean, Background	$M_b = 0$	$M_b = 0$	$M_b = 0.4667$	$M_b = 0.6471$	$M_b = 1.2609$	$M_b = 2.0313$
Variance, Background	$\sigma^2_b = 0$	$\sigma^2_b = 0$	$\sigma^2_b = 0.2489$	$\sigma^2_b = 0.4637$	$\sigma^2_b = 1.4102$	$\sigma^2_b = 2.5303$
Weight, Foreground	$W_f = 1$	$W_f = 0.7778$	$W_f = 0.5833$	$W_f = 0.5278$	$W_f = 0.3611$	$W_f = 0.1111$
Mean, Foreground	$M_f = 2.3611$	$M_f = 3.0357$	$M_f = 3.7143$	$M_f = 3.8947$	$M_f = 4.3077$	$M_f = 5.000$
Variance, Foreground	$\sigma^2_f = 3.1196$	$\sigma^2_f = 1.9639$	$\sigma^2_f = 0.7755$	$\sigma^2_f = 0.5152$	$\sigma^2_f = 0.2130$	$\sigma^2_f = 0$
Within Class Variance	$\sigma^2_W = 3.1196$	$\sigma^2_W = 1.5268$	$\sigma^2_W = 0.5561$	$\sigma^2_W = 0.4909$	$\sigma^2_W = 0.9779$	$\sigma^2_W = 2.2491$

Figure A.6: Table showing thresh values from 0-5

It can be seen that for the threshold equal to 3, al has the lowest sum of weighted variances. Therefore, this is the final selected threshold. All pixels with a level less than 3 are background, all those with a level equal to or greater than 3 are foreground. As the images in the table show, this threshold works well.

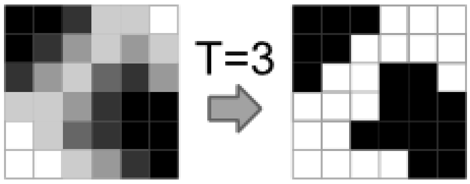


Figure A.7: Thresholded Image

Appendix B

Wavelets

A wavelet is a wave-like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one recorded by a seismograph or heart monitor.
Generally, wavelets are intentionally crafted to have specific properties that make them useful for signal processing. Using convolution, wavelets can be combined with known portions of a damaged signal to extract information from the unknown portions.

B.1 Types of wavelets

1. Haar
2. Daubechies
3. Biorthogonal
4. Coiflets
5. Symlets

Daubechies
Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets thus making discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the surname of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet. Here are the wavelet functions psi of the next nine members of the family:

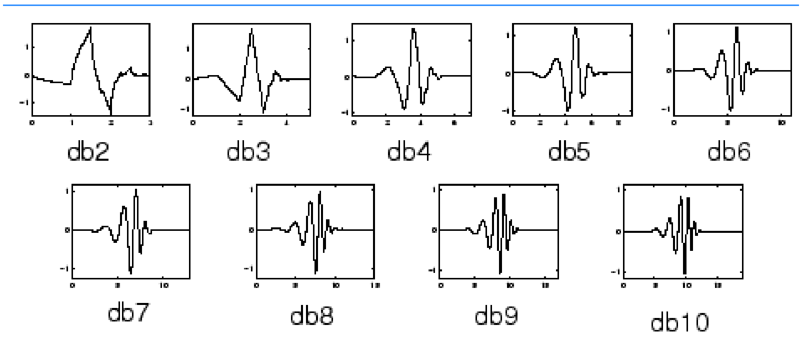


Figure B.1: Wavelet Functions

B.2 Wavelet Implications

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have ad- vantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes.
A wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale.

B.3 Wavelet Toolbox

Wavelet Toolbox provides functions and apps for analyzing and synthesizing signals and images. The toolbox includes algorithms for continuous wavelet analysis, wavelet coherence, synchrosqueezing, and data-adaptive time-frequency analysis. The toolbox also includes apps and functions for decimated and nondecimated discrete wavelet analysis of signals and images, including wavelet packets and dual-tree transforms.
Common applications of wavelet transforms include:

1. Speech and audio processing
2. Image and video processing
3. Biomedical imaging
4. 1D and 2D applications in communications and geophysics

Appendix C

Structuring Elements

An essential part of the morphological dilation and erosion operations is the structuring element used to probe the input image. A structuring element is a matrix that identifies the pixel in the image being processed and defines the neighborhood used in the processing of each pixel. Typically choose a structuring element the same size and shape as the objects you want to process in the input image. For example, to find lines in an image, create a linear structuring element.

C.1 Flat Structuring Element

A flat structuring element is a binary valued neighborhood, either 2-D or multidimensional, in which the true pixels are included in the morphological computation, and the false pixels are not. The center pixel of the structuring element, called the origin, identifies the pixel in the image being processed. Use the strel function to create a flat structuring element. You can use flat structuring elements with both binary and grayscale images. The following figure illustrates a flat structuring element.

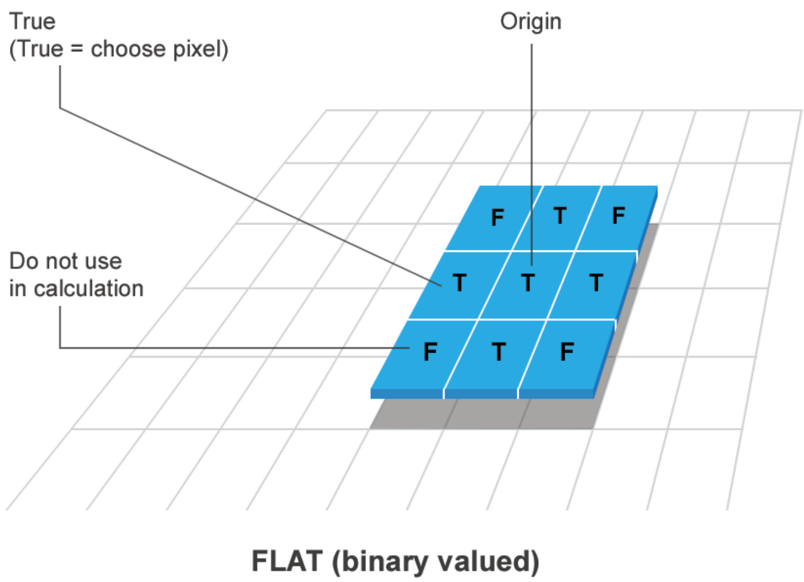


Figure C.1: Flat structuring element

C.2 Non-Flat Structuring Element

A nonflat structuring element is a matrix of type double that identifies the pixel in the image being processed and defines the neighborhood used in the processing of that pixel. A nonflat structuring element contains finite values used as additive offsets in the morphological computation. The center pixel of the matrix, called the origin, identifies the pixel in the image that is being processed. Pixels in the neighborhood with the value -Inf are not used in the computation. Use the offsetstrel function to create a nonflat structuring element. You can use nonflat structuring elements only with grayscale images.

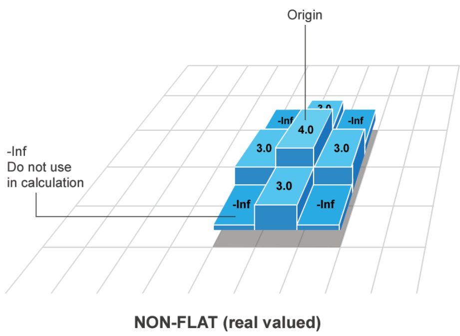


Figure C.2: Non-flat structuring element

C.3 Determine the Origin of a Structuring Element

The morphological functions use this code to get the coordinates of the origin of structuring elements of any size and dimension:

origin = floor((size(nhood)+1)/2)

where nhood is the neighborhood defining the structuring element. To see the neighborhood of a flat structuring element, view the Neighborhood property of the strel object. To see the neighborhood of a nonflat structuring element, view the Offset property of the offsetstrel object. For example, the following illustrates the origin of a flat, disk-shaped structuring element.

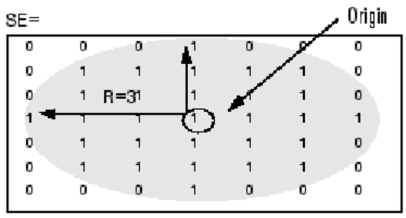


Figure C.3: Disk-shape structuring element