PROJECT REPORT ON

ROI BASED CONTRAST ENHANCEMENT IN MEDICAL IMAGING THROUGH REVERSIBLE DATA HIDING AND MULTI-GROUP STRETCHING

Submitted in partial fulfilment of the Requirement for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

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CERTIFICATE

This is to certify that the dissertation entitled "ROI BASED CONTRAST ENHANCEMENT IN MEDICAL IMAGING THROUGH REVERSIBLE DATA HIDING AND MULTI-GROUP STRETCHING" is being submitted by M. Venkata Deepthi(21095A0430),G.Madhu(20091A0485),K.ShashiKanth(20091A04H3), K.Babu (20091A0412) under the guidance of Mr. K. Anil Kumar, Assistant Professor for Project of the award of B.Tech Degree in Electronics and Communication Engineering, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal (Autonomous) (Affiliated to JNTUA Anantapuramu) is a record of bonafide work carried out by them under our guidance and supervision.

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Signature of the External Examiner

Date of Viva-Voce:

CANDIDATE'S DECLARATION

We hereby declare that the work done in this project titled **"ROI Based Contrast enhancement in medical imaging through reversible data hiding and multi-group stretchng"** submitted for the completion of the main project in the IV Year II Semester of B. Tech (ECE) at **Rajeev Gandhi Memorial College of Engineering and Technology (Autonomous), Nandyal**, is an authentic record of our original work done under the guidance of **Mr.K.Anil Kumar, Assistant Professor**, Dept. of ECE, RGMCET, Nandyal. We have not submitted the material embodied in this main Project for the award of any other degree in any other institution.

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INDEX

CONTENTS **PAGE NO**

INDEX

CONTENTS **PAGE NO**

INDEX

CONTENTS **PAGE NO**

INDEX

CONTENTS **PAGE NO**

List Of Figures

List Of Tables

ABSTRACT

Reversible Data Hiding-based Contrast Enhancement (RDHCE) specifically designed for improving the contrast in medical images. This is an important task as better contrast can help doctors make more accurate diagnoses.

The problem with existing RDHCE methods is that they struggle with accurate segmentation of the Region of Interest (ROI) in medical images.The ROI is the part of the image that is most critical for diagnosis. When the ROI is not segmented accurately, it affects the effectiveness of contrast enhancement. Additionally, some methods have difficulty working with ROI histograms that have very few empty bins on both histogram sides, which effects their ability to enhance contrast.

To address these issues, a new method is proposed, which uses a UNet3+ network model to better segment the ROI. Furthermore, the proposed method introduces a multi-group stretching approach to overcome the limitations related to histogram expansion when there are empty bins on both histogram sides. This method can greatly improve the visual quality of medical images in the field of medical imaging and help doctors in making more accurate diagnoses.

Keywords: Automatic contrast enhancement,reversibledata hiding,ROI segmentation, stretching group.

CHAPTER 1

INTRODUCTION

1.1 Reversible data hiding :

Reversible data hiding (RDH) is a technique used to embed additional data into a cover medium, such as images or videos, while ensuring that the original cover data can be completely recovered without any loss. Unlike traditional data hiding methods, where the embedded data may alter the cover medium irreversibly, RDH allows for reversible extraction of the hidden data without any distortion to the original cover data.

The primary objective of reversible data hiding is to strike a balance between embedding capacity and distortion. Embedding capacity refers to the amount of additional data that can be hidden within the cover medium, while distortion measures the impact of embedding on the quality of the cover data. In RDH, the challenge lies in maximizing the embedding capacity while minimizing the distortion introduced during the embedding process. There are several techniques and algorithms employed in reversible data hiding:

1.1.1 Prediction Error Expansion (PEE) : PEE is a widely used technique in RDH, where prediction errors between the original cover data and its predicted values are expanded to embed additional data. By carefully modifying these prediction errors, it's possible to hide data without causing irreversible distortion to the cover data.

1.1.2 Histogram Modification :Histogram modification techniques manipulate the histogram of the cover data to embed additional information. These methods typically modify the pixel values or intensities in such a way that the changes are reversible, allowing the original histogram to be restored during data extraction.

1.1.3 Lossless Compression: Lossless compression algorithms are used to compress the cover data before embedding additional information. The embedded data is typically added as metadata or auxiliary information during compression, allowing for its reversible extraction without any loss of information.

1.1.4 Difference Expansion: Difference expansion techniques exploit the correlation between adjacent pixel values to embed data. By expanding the differences between neighboring pixel values, additional data can be hidden within the cover data without introducing irreversible distortion.

Overall, reversible data hiding is a valuable technique for various applications where data confidentiality and integrity are paramount. Researchers continue to develop new algorithms and methods to improve the embedding capacity and minimize distortion in reversible data hiding systems.

1.2 Contrast Enhancement:

Contrast enhancement is a digital image processing technique used to improve the visibility of details in an image by increasing the difference in intensity between different regions or objects within the image. It aims to enhance the overall quality of the image by improving its contrast, making it visually more appealing and easier to interpret. Contrast enhancement techniques can be applied to a wide range of photographs, including images, medical images, images of the satellite.

There are various methods and algorithms used for contrast enhancement, some of which include:

1.2.1 Histogram Equalization: Histogram equalization is a popular technique used to enhance the contrast of an image by redistributing the intensity values of its pixels. It works by mapping the pixel intensity values of the original image to a new histogram that is more evenly distributed across the entire intensity range. This helps to stretch out the intensity levels, thereby enhancing the contrast of the image.

1.2.2 Histogram Stretching: Histogram stretching is a simple contrast enhancement technique that involves linearly scaling the intensity values of an image to cover the full dynamic range of available pixel values. This stretching operation expands the intensity range, effectively increasing the contrast of the image.

1.Adaptive Contrast Enhancement: Adaptive contrast enhancement methods dynamically adjust the contrast of different regions within an image based on their local characteristics. These methods often involve dividing the image into smaller regions and applying contrast enhancement techniques independently to each region. This allows for more targeted contrast enhancement, particularly in images with varying lighting conditions or complex backgrounds.

2.Non-linear Contrast Enhancement: Non-linear contrast enhancement techniques apply non-linear transformations to the pixel intensity values of an image to enhance its contrast. These transformations can be based on mathematical functions such as logarithmic, exponential, or power-law functions, which nonlinearly adjust the intensity values to achieve the desired contrast enhancement.

3.Retinex-Based Methods: Retinex-based methods simulate the human visual system's ability to perceive differences in brightness and color under varying lighting conditions. These methods aim to enhance the contrast and brightness of an image by separating its illumination and reflectance components and adjusting them independently to achieve better contrast enhancement.

Contrast enhancement is widely used in various applications, including image enhancement for photography, medical image analysis, remote sensing, and computer vision tasks. While contrast enhancement techniques can significantly improve the visual quality of images, care must be taken to ensure that the enhancements do not introduce artifacts or distortions that may affect the interpretation of the underlying information.

Region of Interest (ROI) and Non-Region of Interest (NROI) are concepts frequently used in medical image analysis to differentiate between areas of interest and background regions within an image. Here's a detailed explanation of both terms:

1.3 ROI and NROI of medical images:

1.3.1 Region of Interest (ROI):

•In medical imaging, a Region of Interest (ROI) refers to a specific area or region within an image that is of particular interest for analysis, diagnosis, or further processing.

•ROIs are typically identified based on their relevance to the specific medical condition being studied or the diagnostic task at hand. For example, in radiology, an ROI might correspond to a tumor, lesion, anatomical structure, or any area requiring closer examination.

•ROIs can be manually delineated by medical professionals or automatically identified using segmentation algorithms and techniques. Once identified, ROIs can be extracted for further analysis, measurement, or feature extraction.

•The analysis of ROIs plays a crucial role in medical image interpretation, as it helps medical professionals focus on relevant areas and make more accurate diagnoses.

1.3.2 Non-Region of Interest (NROI):

•Non-Region of Interest (NROI), as the name suggests, refers to the background or areas of the image that are not considered relevant for the analysis or diagnosis.

•NROIs typically include areas surrounding the ROIs, as well as regions containing noise, artifacts, or irrelevant structures.

•In medical image analysis, NROIs are often excluded or masked out to reduce noise and focus computational resources on processing the ROIs.

• While NROIs may not be directly relevant for the diagnostic task at hand, they still play a role in providing context and ensuring the completeness of the image dataset.

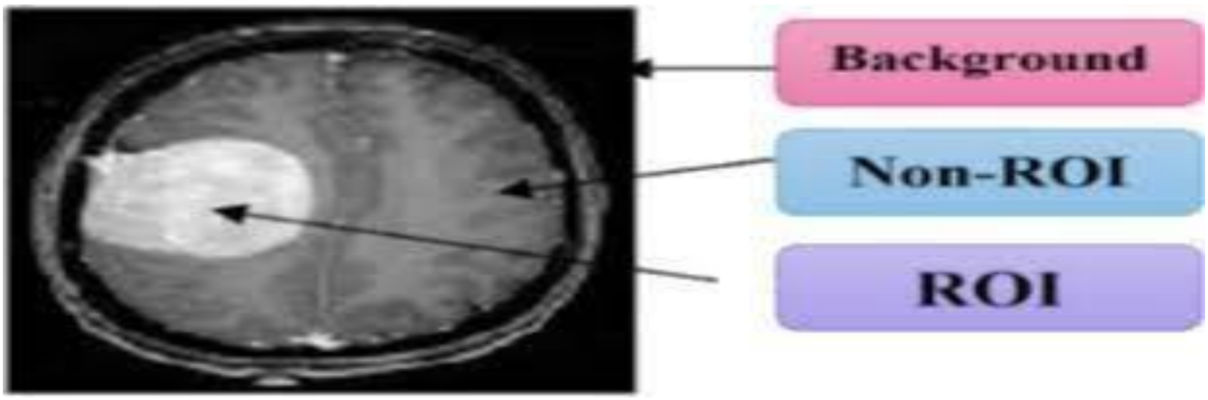

Figure 1.1 :ROI and NROI of medical images

1.4 Unet3+ Network model:

The "UNet3+" isn't a widely recognized term in the field of neural networks as of my last update. However, I can provide a hypothetical explanation based on common practices and principles:

UNet is a type of neural network architecture used for tasks like image segmentation, where the goal is to outline specific objects or regions within an image. It's called "UNet" because of its U-shaped architecture, which consists of an encoder pathway to capture features and a decoder pathway to generate segmented output.

Now, let's imagine what "UNet3+" could represent:

Feature of UNet3+:

• ***Increased Depth :*** **"**3+" might suggest a deeper architecture compared to the original UNet, possibly with additional layers or features.

• ***Enhanced Skip Connections***: UNet3+ could include improved skip connections to better preserve spatial information and facilitate feature learning.

• ***Attention Mechanisms:*** Incorporating attention mechanisms could allow UNet3+ to focus on important regions of the input image, improving segmentation accuracy.

• ***Multi-Scale Feature Fusion:*** UNet3+ might integrate features from multiple scales to capture both local and global context effectively.

• ***Regularization Techniques:*** To prevent overfitting, UNet3+ might use techniques like dropout or batch normalization.

• ***Advanced Activation Functions:*** Using modern activation functions could help UNet3+ learn more complex patterns in the data.

• UNet3+ could find applications in various fields requiring image segmentation, such as medical imaging, satellite imagery analysis, and autonomous driving.

• While "UNet3+" isn't a standard model, hypothetically, it represents a more advanced version of UNet with additional features and capabilities. Its potential improvements could lead to better performance and broader applicability in real-world scenarios.

CHAPTER 2

LITERATURE SURVEY

In the paper Enhancing Reversible Data Hiding Using Dual Pairwise Prediction-Error Expansion, Reversible Data Hiding (RDH) techniques aim to embed additional information into a cover medium while ensuring that the original information can be fully recovered with no loss. Prediction-Error Expansion (PEE) has emerged as a powerful mechanism within RDH, leveraging the inherent redundancy in the cover medium. While pairwise PEE had been proposed mainly to join and modify prediction errors for minimum degradation, and exists room for further improvement. In response, this paper introduces a novel strategy called dual pairwise PEE, designed to fully exploit the potential of pairwise PEE.

The motivation behind dual pairwise PEE stems from the observation that the majority of embedding capacity arises from individually expanding only one pairing error. To harness this potential, the paper proposes a method to identify separable error-pairs, where one error can be shifted independently. These separable error-pairs are then optimized for error modification. Specifically, the paper suggests recalculating and collecting the remaining error after shifting any one pairing error, thereby forming an error sequence.

Subsequently, by considering pairs of neighbouring errors within the sequence, a new set of error-pairs suitable for double pairwise PEE is derived. This approach effectively doubles the capacity for error modification compared to original pairwise PEE. The enhanced capacity is attributed to the improved exploitation of error correlation.

Experimental results demonstrate the effectiveness of the proposed dual pairwise PEE scheme. Comparative analysis showcases its superiority over several state-of-the-art RDH approaches. Notably, the scheme achieves better capacity-distortion performance, highlighting its practical significance in real-world applications.

This paper presents a comprehensive framework for RDH based on dual pairwise PEE. It begins by leveraging the correlation among the largest/smallest three pixels in a block to generate error-pairs. Furthermore, the original embedding technique is extended into double-layered embedding to enhance prediction-error generation. This extension facilitates the determination of the optimal spatial location for each block.

Moreover, the paper optimizes the utilization of separable error-pairs, particularly focusing on those containing at least one shiftable error. By recalculating and combining errors into pairs, the proposed double pairwise PEE strategy significantly enhances error correlation exploitation.

Experimental evaluations validate the efficacy of the proposed scheme, demonstrating its superiority over existing state-of-the-art approaches. The scheme's ability to achieve superior capacity-distortion performance underscores its practical relevance and potential for various RDH applications.

Reversible data hiding in encrypted images (RDHEI) is a crucial technique for ensuring data security. However, many existing RDHEI methods struggle to achieve desirable payload levels. To overcome this limitation, this paper proposes a new RDHEI method employing hierarchical embedding. The contributions of the work are two fold:

(1) A novel technique for hierarchical label map generation is introduced for the bit-planes of plaintext images. This hierarchical label map, calculated using prediction techniques, is compressed and embedded into the encrypted image.

(2) Hierarchical embedding is devised to achieve a high embedding payload. This approach divides prediction errors into 3 categories: small magnitude, medium magnitude, and finally large-magnitude, each named with different labels. Unlike conventional methods, pixels with small- magnitude/large-magnitude prediction errors are both utilized to accommodate secret bits, thereby enabling a high embedding payload.

Experiments conducted on two standard datasets validate the proposed RDHEI method. The results demonstrate its superiority over some state-of-the-art RDHEI methods in terms of payload capacity. The average payloads achieved by the proposed method are 3.68 bits per pixel (bpp) and 3.623 bpp for the BOWS-2 and BOSSbase datasets, respectively.

This paper presents a novel approach to RDHEI based on hierarchical embedding, offering error-free data hiding with a significantly enhanced payload capacity. A key innovation lies in the development of a hierarchical label map generation technique, crucial for bit-plane processing of plaintext images. The hierarchical label map which is derived using advanced prediction techniques undergoes compression & subsequent embedding into the encrypted images.

Furthermore, hierarchical embedding is introduced to exploit prediction errors effectively, thereby maximizing the embedding payload. This embedding strategy categorizes prediction errors into three distinct magnitudes: small, medium, and large. Each category is assigned a unique label for identification. Notably, unlike conventional approaches, pixels associated with both small-magnitude and large-magnitude prediction errors contribute to accommodating secret bits, thereby optimizing the embedding capacity.

Extensive experiments have been conducted to validate the proposed RDHEI method's efficacy. The results underscore its superiority over several state-of-the-art RDHEI techniques, particularly in terms of payload capacity. On the BOWS-2 and BOSSbase datasets.

In summary, the proposed RDHEI method offers a robust solution for secure data embedding in encrypted images, leveraging hierarchical embedding to achieve superior payload capacity. The innovative techniques introduced, including hierarchical label map generation and error categorization, contribute to its effectiveness and performance superiority over existing methods.

Histogram modification is a widely explored technique in reversible data hiding (RDH), with recent attention focusing on multiple histograms modification (MHM) due to its promising embedding performance. However, the original MHM approach has limitations in achieving high embedding capacity, as it restricts the maximum modification on each pixel value to 1 and allows expansion for only two pair of bins in the prediction error histogram (PEH). To address this constraint and enable high-capacity embedding, this paper proposes an extended MHM scheme with an efficient solution.

Specifically, the proposed method allows for a larger modification amplitude per pixel and utilizes multiple pairs of bins for expansion within each PEH. Moreover, an advisable expansion bin selection strategy is introduced to optimize embedding performance. This strategy enables adaptive embedding across different PEHs, with low-index PEHs carrying more data bits than high-index ones, based on the sharpness of their distributions.

Additionally, the paper presents a simplified parameter determination approach to efficiently seek optimal solutions with low computational complexity. Experimental results demonstrate that the proposed method achieves high embedding capacity and outperforms several state-of-the-art RDH methods.

This paper introduces a high-capacity RDH method based on an extension of the MHM technique. Unlike the original MHM approach, which imposes a maximum modification limit of 1 per pixel and restricts expansion to only one pair of bins per PEH, the proposed method relaxes these constraints. By allowing larger modification amplitudes per pixel and utilizing multiple pairs of bins for expansion within each PEH, the proposed approach significantly enhances embedding capacity.

An important aspect of the proposed method is the introduction of an advisable embedding strategy, which facilitates adaptive embedding across different PEHs. This strategy prioritizes low-index PEHs, which contain smoother pixel distributions, for carrying more data bits compared to high-index PEHs. This adaptive approach optimizes embedding performance and ensures efficient utilization of available capacity.

Furthermore, the paper presents a simplified parameter optimization technique, which enables the determination of optimal parameters with low computational complexity. This contributes to the practical feasibility of the proposed method in real-world applications.

Overall, the contributions of this paper can be summarized into two key aspects. Firstly, it introduces the concept of multiple bin expansion within a single PEH, enhancing embedding capacity. Secondly, it proposes efficient principles for parameter optimization in high-capacity MHM, demonstrating effectiveness through comprehensive evaluations.

In conclusion, this work addresses the challenge of extending MHM for high-capacity embedding while maintaining acceptable computational complexity. The proposed method offers a practical solution for RDH applications, significantly enhancing embedding capacity and outperforming existing state-of-the-art methods.

State-of-the-art models for medical image segmentation, such as variants of U-Net and fully convolutional networks (FCN), have demonstrated significant success. However, they suffer from two main limitations:

(1) the optimal depth of these models is not known a priori, necessitating either extensive architecture search or inefficient ensembling of models with varying depths, and

(2) their skip connections enforce a restrictive fusion scheme, limiting aggregation to feature maps of the same scale in the encoder and decoder sub-networks. To cross these limitations, the proposed UNet++, a novel neural architecture for semantic and instance segmentation.

1. Alleviating the unknown network depth through an efficient ensemble of U-Nets with varying depths, which share an encoder partially and co-learn using deep supervision simultaneously.

2. Redesigned all skip connections mainly to aggregate features of vary semantic scales at the decoder sub networks, enabling the flexible feature fusioned scheme.
3. Introducing a pruning scheme to accelerate the inference speed of UNet++. We evaluate UNet++ across six diverse medical image segmentation datasets, encompassing multiple imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and electron microscopy (EM). Our evaluation demonstrates that:

1. UNet++ consistently outperformsbaseline models for semantic segmentation across different datasets and backbone architectures.
2. UNet++ improves segmentation quality for objects of varying sizes compared to fixed-depth U-Net.
3. Mask RCNN++ (Mask R-CNN with UNet++ design) surpasses the original Mask R-CNN for instance segmentation.
4. Pruned UNet++ models achieve significant speedup while exhibiting modest performance degradation.

In conclusion, UNet++ presents a novel architecture for more accurate image segmentation. Its improved performance is attributed to its nested structure and redesigned skip connections, which address the challenges of unknown optimal architecture depth and unnecessarily restrictive skip connection design in U-Net. Evaluation across various biomedical imaging applications demonstrates consistent performance improvement over state-of-the-art backbones for both semantic and instance segmentation tasks.

Surface water is a critical resource for human survival and environmental sustainability, with accurately delineated hydrologic streamlines playing pivotal role in various scientific domains. These streamlines are essential for tasks such as assessing water resources, modelling climate changes, evaluating agricultural suitability, mapping flood inundation, and monitoring environmental changes. However, conventional approaches to streamline detection often struggle to incorporate information from the complex three-dimensional (3D) environment of streams and land surface features.

In recent years, the availability of high-accuracy lidar data has provided an opportunity to derive both 3D information and terrestrial surface reflectance, offering potential for more precise streamline detection. This study addresses this opportunity by developing an attention U-net model tailored for utilizing high-accuracy lidar data to detect hydrologic streamlines. The attention U-net model is a deep learning architecture known for its effectiveness in image segmentation tasks.

The developed model leverages lidar-derived feature maps to accurately detect streamlines. It addresses the challenges associated with stream detection by treating it as an image segmentation problem, where streamlines are classified against non-stream pixels. This problem is inherently challenging due to the complex processes involved in streamline formation and the spatial heterogeneity of surface water features.

Traditional machine learning methods, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), often struggle with multi-scale

context information, such as topology, land cover distribution, and topography. In contrast, the attention U-net model excels in handling such complex information, leading to improved streamline detection accuracy.

The evaluation of the attention U-net model against baseline machine learning methods demonstrates its superior performance, achieving an average F1 score improvement of 11.29%. Additionally, the attention U-net model produces streamlines with better smoothness and connectivity between classified streamline channels, further highlighting its effectiveness.

In conclusion, this research presents a novel approach for hydrologic streamline detection using high-accuracy lidar data and the attention U-net model. By effectively leveraging lidar-derived feature maps and advanced deep learning techniques, the proposed method offers significant improvements over traditional machine learning methods. These findings underscore the potential of deep learning approaches in harnessing high- accuracy lidar data for fine-scale hydrologic streamline detection, with broad implications across various scientific domains.

CHAPTER 3

BASICS OF DIGITAL IMAGE PROCESSING

Digital imaging transforms physical photographs into electronic formats compatible with computers, facilitating effortless storage, manipulation, and sharing, thereby enhancing their utility and convenience in the modern digital era.

3.1 Image

Images play a fundamental role in human communication, perception, and cognition. They are used extensively in fields such as art, design, science, medicine, engineering, and entertainment to convey complex concepts, document events, express creativity, facilitate understanding, and evoke emotions..

Figure 3.1: Image

3.2 Digital images types

There are four types of digital images.

- Binary Images
- Gray Scale Images
- Color Images
- Indexed Images

Image can be described as a function ***f*** where **x** belongs to [a,b] and y belongs to [c,d] which returns as output ranging between maximum and minimum pixel intensity values. So, it can be stated as,

f:[a,b] * [c,d]-> [min,max]

3.2.1 Binary Images:

f:[a,b] * [c,d]-> 0 or 255

Binary images play a crucial role in image processing by representing visual data in a simplified format where each pixel is either black or white, representing foreground and background, respectively. This format is essential for various image processing tasks like object detection, segmentation, and pattern recognition. It allows for efficient storage, manipulation, and analysis of visual data, enabling the development of sophisticated algorithms for tasks such as optical character recognition, medical image analysis, and industrial automation.

3.2.2 Grey Scale Images:

f:[a,b] * [c,d]-> [min,max]

Grayscale images find widespread use in image processing tasks due to their simplicity and efficiency. They are commonly employed in applications such as medical imaging, document scanning, facial recognition, and feature extraction.One significant advantage of grayscale images is their reduced data complexity compared to color images, making them more computationally efficient to process. Additionally, many image processing algorithms and techniques are designed specifically for grayscale images, enabling a wide range of analysis and manipulation tasks.

3.2.3 Color Images:

Color images are digital representations where each pixel contains color information composed of multiple channels, typically representing red, green, and blue (RGB) components. These channels combine in varying intensities to produce a wide spectrum of colors, enabling the faithful reproduction of real-world scenes and objects.

In a color image, each pixel's color is determined by the intensity values of its RGB channels. These values typically range from 0 to 255 in an 8-bit image, with 0 indicating no contribution and 255 indicating full intensity for each channel. By combining different intensities of red, green, and blue, color images can represent a vast array of hues, shades, and tones.

3.2.4 Indexed Images :

Indexed images are a type of digital image representation where each pixel value corresponds to an index in a color lookup table (CLUT) or palette. Instead of directly encoding color information for each pixel, indexed images store a limited set of colors in a palette and assign an index value to each pixel to indicate its color.

3.3 Image Digitization

An picture captured by a sensor is expressed as a continuous function f(x,y). To process a caught picture by PC it must be spoken to in frame work structure. A matrix is the most widely recognized information structure for low level representation of a picture. Components in the network are whole numbers relating to spendour or to another property of the compared pixel in the inspecting lattice. Picture data frame work is available through the directions of a pixel that compare with the line and segment records. Picture digitization implies that the capacity f(x,y) is inspected frame work with M lines and N segments.

3.3.1 Sampling

A continuous picture function f(x,y) can be examined using a discrete network of testing focuses in the picture plane. A second possibility is to extend the picture capacity utilizing some orthogonal capacity as a base Fourier change. A continuous picture is digitized at sampling focuses. These inspecting focuses are requested in the plane and their geometric connection is known as the GRID. The computerized picture is then an information structure, for the most part a grid. Matrices utilized as part of a practice or typically square and hexagonal. One endlessly little inspecting point in the lattice compares to one picture component in the advanced picture. The set of pixels together covers whole picture. The pixel is a unit, which is not further separable from the picture investigation perspective. A continuous picture is digitized at sampling focuses. A continuous picture function f(x,y) can be inspected utilizing a discrete network of testing focuses in the picture plane.

3.3.2 Quantization

Quantization is a process of round off the continuous range of values to a discrete set of values. In the context of image processing, quantization involves converting the continuous range of pixel intensity values in an analog image into a finite set of discrete intensity levels in a digital image.

During quantization, the continuous intensity values captured during sampling are rounded or approximated to the nearest value in the quantization levels. The number of quantization levels determines the precision or fidelity of the digital representation of the image.

For example, in grayscale images, quantization typically involves mapping the continuous range of pixel intensity values, which can span from 0 (black) to 255 (white), into a smaller set of discrete intensity levels, such as 0 to 7 or 0 to 15. Each pixel in the digital image is then assigned one of these discrete intensity levels based on its sampled intensity value.

In color images, quantization is applied independently to each color channel (e.g., red, green, blue) to map the continuous range of color values into discrete levels for each channel.

Quantization is a fundamental step in the digitization of images and plays a crucial role in reducing the amount of data required to represent an image digitally while preserving its visual quality to a satisfactory level. However, quantization can introduce quantization errors or loss of information, particularly when the number of quantization levels is low or when aggressive compression techniques are applied. Therefore, careful consideration of quantization parameters is necessary to balance data compression and image quality requirements.

3.4 Fundamental Steps in Digital Image Processing

There are some fundamental steps. But as they are fundamental, The fundamental steps are described in the fig 3.4 as shown below.

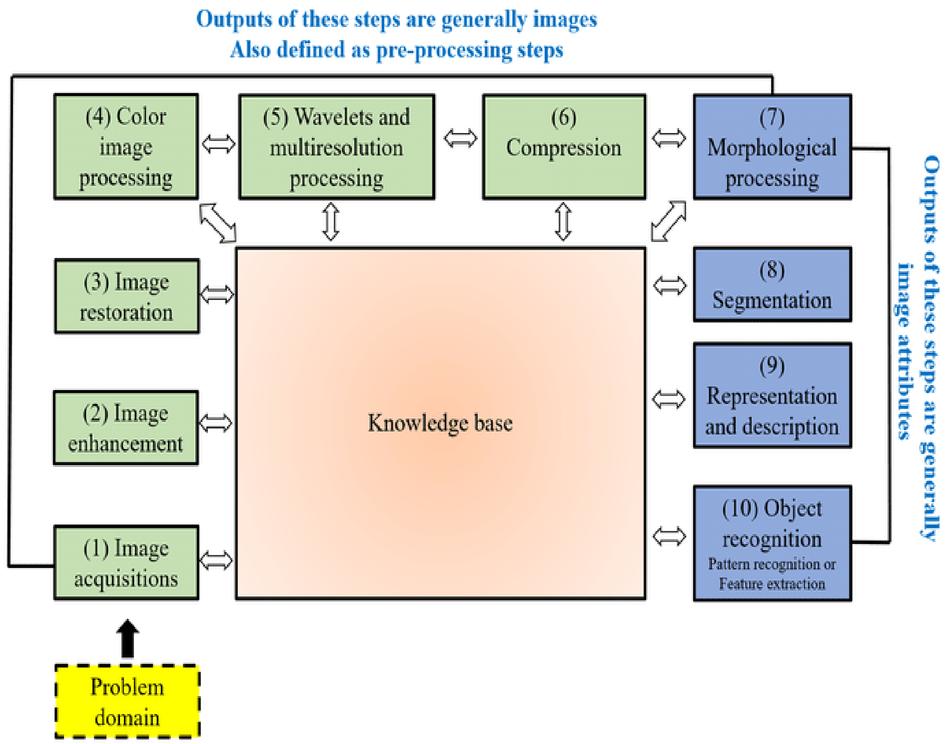

Fig 3.2 : Fundamentals of digital image processing

3.4.1 Acquisition in image processing

In image processing, acquisition refers to the process of capturing or obtaining images from various sources such as cameras, scanners, or sensors. It involves converting real-world scenes or objects into digital representations that can be manipulated, analyzed, and stored using computers acquisition is the foundational step in image processing, providing the raw data necessary for subsequent analysis, interpretation, and manipulation of digital images. The quality and fidelity of acquired images play a crucial role in the effectiveness and accuracy of downstream image processing tasks.

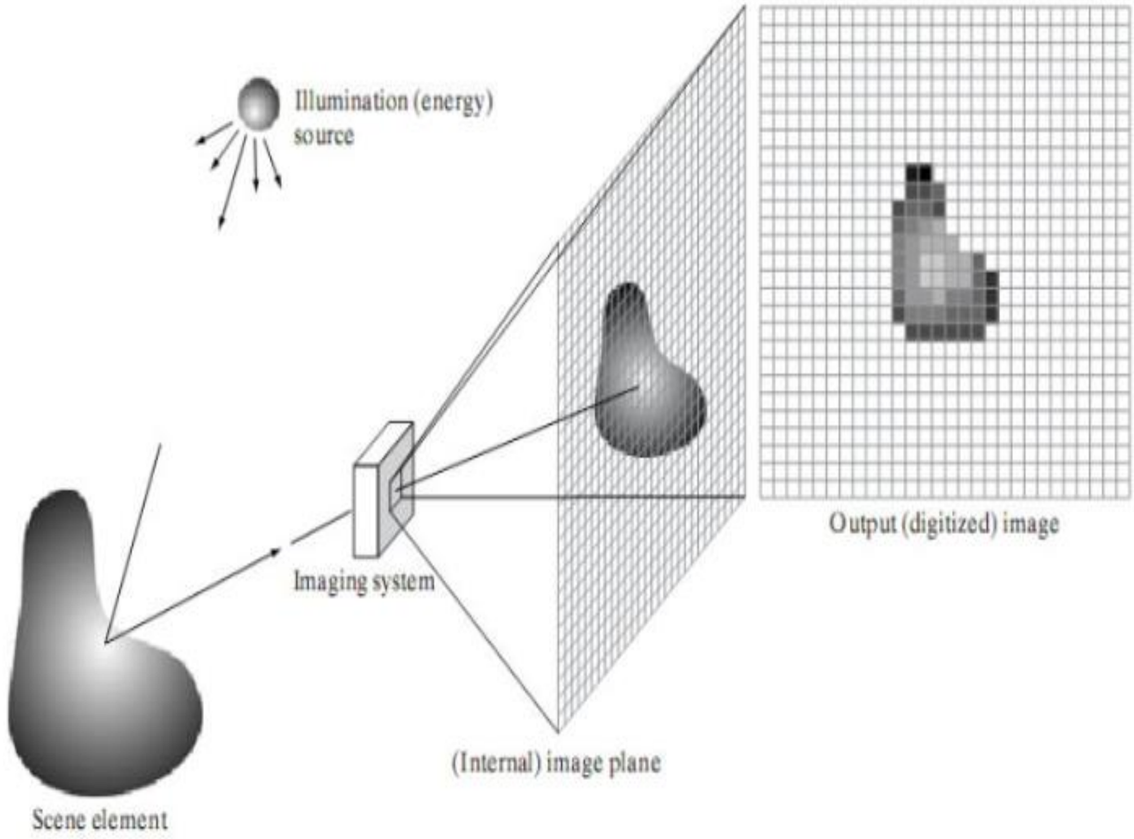

Fig 3.3 Image aquisition

3.4.2 Enhancement in image processing

Image enhancement is a fundamental process in image processing aimed at improving the visual quality and interpretability of digital images. It encompasses a range of techniques such as contrast adjustment, brightness adjustment, color adjustment, noise reduction, sharpness enhancement, and

image filtering. These techniques are applied sequentially or in combination to enhance different aspects of the image, such as improving contrast, reducing noise, or sharpening details. Image enhancement finds applications in various fields, including photography, medical imaging, satellite imaging, forensic analysis, surveillance, and digital art, where it facilitates better visualization, analysis, and communication of visual information. Software tools and algorithms are available for performing image enhancement, allowing users to adjust and manipulate images to achieve desired results. Evaluation of image enhancement techniques can be done subjectively through visual inspection or objectively using quantitative metrics, ensuring the effectiveness and quality of the enhancement process.

Fig 3.4: Image Enhancement Process

3.4.3 Image Restoration in image processing

Image restoration in image processing is the process of improving the quality of a degraded or damaged image to restore it to a more visually pleasing or usable state. This restoration is essential in various fields where image quality is crucial for accurate analysis and interpretation. Understanding the degradation model is the first step in image restoration, as it helps in developing effective techniques to reverse or compensate for the effects of degradation. These techniques encompass a range of methods, including deblurring to remove blur, denoising to reduce noise, inpainting to fill in missing or damaged regions, super-resolution to enhance resolution, and deconvolution to recover the original image from its degraded version. These algorithms can be classical or modern, employing mathematical models or deep learning approaches, respectively, to restore images effectively. Image restoration finds applications in fields such as photography, medical imaging, satellite imaging, surveillance, forensics, and archival restoration, where it enhances visual quality, interpretability, and utility. The effectiveness of image restoration techniques is evaluated through both qualitative visual inspection and quantitative measures, ensuring the restored images meet the required standards for analysis, communication, and decision-making.

Fig 3.5: Restored Image

3.4.4: Color Image Processing

Color image processing in digital image processing involves the manipulation, analysis, and enhancement of images that contain color information. In this process, color images are typically represented using multiple channels, commonly in the RGB (Red, Green, Blue) color model, where each pixel contains intensity values for the red, green, and blue color channels. Beyond RGB, various other color spaces such as CMYK, HSV, LAB, and YUV are used, offering different ways to represent and manipulate color information to cater to specific requirements. Color enhancement techniques are employed to improve the visual quality of color images by adjusting the some attributes like color balance, saturation, contrast, and brightness, either globally or locally to specific regions of interest. Moreover, color segmentation is utilized for partitioning images into regions based on color similarity, facilitating tasks like object detection and image segmentation. Color filtering and transformations involve applying filters or mathematical operations to manipulate color components, including color space conversions, histogram equalization, color correction, and channel manipulation. Color image compression techniques are also employed to reduce storage space while preserving visual quality, exploiting redundancies and removing irrelevant details. Across various fields such as photography, digital art, medical imaging, remote sensing, computer vision, and multimedia, color image processing finds applications in image editing, color correction, image

Fig 3.6 :Color image processing

analysis, and visualization, contributing to advancements in research, industry, and entertainment.

3.4.5 Wavelet & Multi-Resolution in image processing

Wavelet processing in image analysis involves decomposing an image into various frequency components using wavelet transforms. Unlike Fourier transforms, which break down signals into sinusoidal components at different frequencies, wavelet transforms break down signals into wavelets that are localized in both frequency and time. This localization property enables wavelet transforms to capture both high-frequency details and low-frequency trends in an image simultaneously. Wavelet processing finds applications in tasks such as image compression, denoising, edge detection, and texture analysis. On the other hand, multi-resolution processing involves analyzing an image at multiple levels of detail or resolution. This is achieved by creating a pyramid-like representation of the image, with the original image at the base and progressively downsampled versions at higher levels. Each level of the pyramid represents the image at a different scale, capturing various levels of detail. Multi-resolution processing enables efficient analysis of images at different resolutions, facilitating tasks such as image registration, feature extraction, and image fusion. Techniques like Laplacian pyramids and Gaussian pyramids utilize multi-resolution processing for image decomposition and reconstruction.

3.4.6 Compression in image processing

Compression in image processing is the practice of reducing the size of an image file while maintaining its visual quality to an acceptable level. This process is vital for efficiently storing and transmitting large volumes of image data. Two main types of compression techniques are employed: lossless compression and lossy compression. Lossless compression algorithms aim to decrease file size without any loss of information, achieved by identifying and eliminating redundancy within the image data. Common lossless methods include run-length encoding (RLE) and Huffman coding. But on the other side, lossy compression techniques, like JPEG compression, sacrifice some image quality to achieve higher compression ratios. These algorithms exploit characteristics of the human visual system to remove less noticeable information. While lossy compression is commonly used in digital photography and web graphics due to its higher compression ratios, lossless compression is preferred in fields such as medical imaging and document storage where preserving every detail is critical. Compression in image processing offers benefits such as reduced storage requirements and faster transmission over networks. However, it's essential to strike a balance between compression ratios and acceptable levels of image quality degradation to ensure that compressed images remain visually usable for their intended applications.

3.4.7 Morphological in image processing

Morphological processing is a fundamental technique in digital image processing that revolves around analyzing and manipulating shapes and structures within an image using mathematical morphology principles. At its core, this technique involves operations based on the mathematical theory of morphology, which focuses on studying shapes and their transformations. The primary operations in morphological processing include erosion and dilation. Erosion is a morphological operation that contracts or erodes the boundaries of objects in an image by replacing each pixel with the minimum pixel value within the region covered by a predefined structuring element. Conversely, dilation expands or dilates the boundaries of objects by replacing each pixel with the maximum pixel value within the structuring element's region. These operations are foundational and serve various purposes such as smoothing object boundaries, separating connected objects, filling in gaps, and enhancing object boundaries. Additionally, morphological processing encompasses other operations like opening, closing, boundary extraction, and morphological filtering. Opening combines erosion followed by dilation and is effective for removing small objects and noise, while closing combines dilation followed by erosion and fills in small gaps and holes in objects. Boundary extraction operations extract object outlines, while morphological filtering is used for noise reduction and feature extraction. Overall, morphological processing offers a powerful framework for shape-based analysis and manipulation of images.

3.4.8 Segmentation in image processing

Segmentation in digital image processing involves dividing an image into distinct regions or segments based on various criteria like pixel intensity, color, texture, or spatial proximity. The primary objective of segmentation is to partition the image into cohesive and homogeneous regions that encapsulate meaningful objects, structures, or areas of interest. This process is crucial in numerous image processing tasks, including object detection, image analysis, and computer vision. By accurately segmenting an image, valuable information can be extracted, paving the way for further analysis and processing. However, segmentation can pose challenges, particularly in scenarios with noise, occlusions, or intricate object shapes. The selection of appropriate segmentation techniques depends on the specific characteristics of the image and the requirements of the application, often necessitating experimentation and expertise in the respective domain.

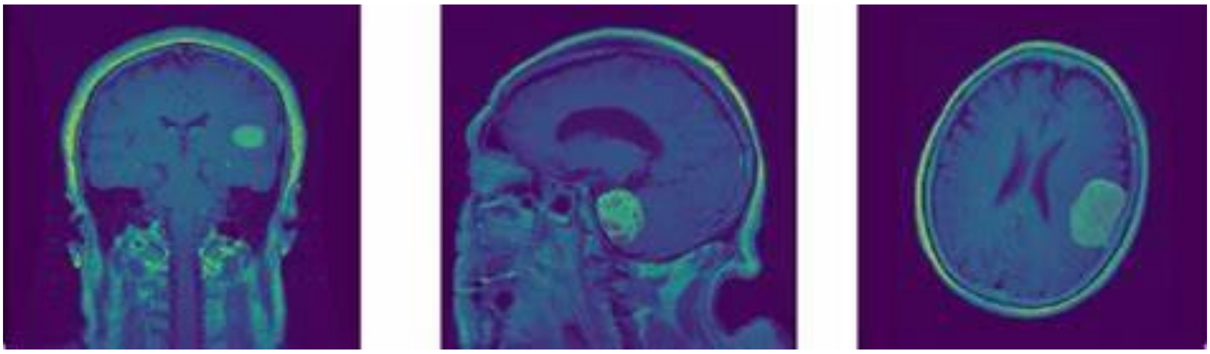

Figure 3.7 : Image Segment Process

3.4.9 Representation and Description in image processing

Representation and description in digital image processing involve transforming the raw pixel data of an image into a suitable format and quantifying its features for further analysis or recognition tasks. Representation encompasses converting the image into a different color space or encoding it using feature descriptors such as histograms or gradients, tailored to the specific characteristics of the image and analysis requirements. On the other hand, description involves extracting and quantifying visual features such as edges, corners, textures, or shapes using techniques like edge and corner detection, texture analysis, and shape descriptors. These features are represented using numerical descriptors or feature vectors, facilitating tasks like object recognition, image retrieval, and pattern recognition in fields like computer vision. Effective representation and description enable the extraction of meaningful information from images, aiding in the identification and analysis of objects or patterns of interest.

3.4.10 Object Recognition in image processing

Object recognition in digital image processing entails the task of recognizing and categorizing objects or patterns present within an image or scene. This process encompasses detecting and pinpointing objects of interest while classifying them into predefined categories or classes. The applications of object recognition span across diverse domains such as computer vision, robotics, autonomous driving, surveillance, medical imaging, and augmented reality. Through object recognition, machines gain the ability to comprehend and interpret visual information, empowering them to interact with their surroundings intelligently and independently.

3.4.11 Knowledge Base in image processing

A knowledge base acts as a central hub where information and expertise are stored, organized, and made readily accessible. It functions as a repository or database structured to facilitate easy retrieval and searching, making it a valuable resource for both individuals and organizations. By capturing and preserving knowledge, it enhances productivity, efficiency, and decision-making processes. This resource plays a crucial role in sharing expertise within a community or organization, ultimately contributing to improved problem-solving capabilities and overall effectiveness.

3.5 Thresholding :

Thresholding is a fundamental technique in image processing used to separate objects or regions of interest from the background by applying a threshold value to pixel intensities. It's a crucial step in image segmentation, where the goal is to partition an image into meaningful regions for further analysis. Thresholding simplifies an image by converting it into a binary image, where pixels are classified as either foreground (object) or background based on their intensity levels compared to the threshold value.

Here's an overview of thresholding and its types:

3.5.1 Global Thresholding:

In global thresholding method , a single value is applied to the complete image. Pixels having the intensity values above the threshold are called as foreground, while those below are classified as background. This method works well when the foreground and background intensities are well-separated.

3.5.2 Adaptive Thresholding:

Unlike global thresholding, adaptive thresholding computes different thresholds for different regions of the image. It's useful in scenarios where lighting conditions vary across the image or when the image contains regions with varying contrasts. Adaptive thresholding methods compute local thresholds based on the intensity distribution within a neighborhood around each pixel.

3.5.3 Otsu's Thresholding:

Otsu's method automatically computes an optimal threshold value to separate foreground and background pixels. It minimizes the intra-class variance or maximizes inter-class variance of pixel intensities, effectively separating the two classes.Otsu's method is particularly useful when the histogram of the image is bimodal, i.e., contains two distinct peaks.

3.5.4 Multi-level Thresholding:

Multi-level thresholding extends thresholding to segment images into more than two levels or classes.Instead of a single threshold, multiple threshold values are used to partition the image into multiple segments based on intensity ranges. It's beneficial for segmenting images with multiple objects or regions of interest with different intensity levels.

3.5.5 Color Thresholding:

Color thresholding is applied to color images where each pixel has multiple color channels (e.g., RGB, HSV).It involves setting thresholds for each color channel to classify pixels based on their color properties.Color thresholding is useful for segmenting objects based on their color characteristics.

Thresholding is a versatile technique used in various applications such as object detection, image segmentation, and image analysis. Choosing the appropriate thresholding method depends on factors such as image characteristics, noise levels, and desired segmentation accuracy. Each thresholding method has its advantages and limitations, and selecting the most suitable method requires understanding the specific requirements of the task at hand.

CHAPTER 4

PROJECT DESCRIPTION

4.1 Existing method:

The rise of digital communication has led to an increase in sharing complex data and multimedia over networks, raising concerns about privacy. Steganography, a technology to hide information, emerged to address this need.

Researchers have focused on reversible data hiding (RDH) to securely store data while preserving original image quality. RDH methods aim to increase data capacity and maintain image quality, typically falling into three categories: lossless compression, difference expansion, and histogram shifting.

Traditionally, RDH methods evaluate quality using peak signal-to-noise ratio (PSNR). However, high PSNR doesn't always mean good visual quality, especially for low-contrast images. Researchers started exploring RDH methods combined with contrast enhancement, known as reversible data hiding-based contrast enhancement (RDHCE).

In the medical field, RDHCE is crucial for enhancing image contrast while preserving patient data. Medical images contain regions of interest (ROIs) providing organ details and non-interest regions (NROIs). Existing RDHCE methods face challenges in accurately enhancing ROI without distorting NROI.

To address these issues, various RDHCE methods have been proposed, focusing on histogram modification to embed data and enhance contrast. However, they often rely on single metrics for segmentation and struggle with complex medical images.

Moreover, existing histogram stretching methods have limitations in adjusting histogram ranges, affecting embedding capacity and contrast enhancement

To overcome these challenges, a new RDHCE method called MGSRDHCE is proposed.

This method integrates deep learning for ROI segmentation, improving accuracy. It also introduces an enhanced histogram stretching technique to maximize histogram equalization. The resulting medical images have higher contrast and greater data capacity compared to existing methods.

In summary, this paper proposes a novel approach combining deep learning segmentation with RDHCE, enhancing contrast in medical images while preserving data integrity. The following sections detail related research, the proposed method, experimental results, and concluding remarks.

In current research, traditional threshold-based techniques, such as Otsu and ATD, are commonly employed to extract the Region of Interest (ROI) from medical images. These methods function by segmenting the ROI based on the gray values of pixels and subsequently selecting eligible pixels according to a predetermined threshold value. However, a notable challenge arises in practical applications where the selected pixels may not be clustered together in a contiguous area within the image. Moreover, altering only the gray values of these selected pixels can result in distortion.

To address this issue, certain methodologies have been proposed. These methodologies involve dividing the pixels on a line-by-line basis to identify the first and last selected pixels following the threshold segmentation process. Subsequently, the ROI is constructed by encompassing all pixels situated between the first and last pixels of each row. This approach ensures that the resulting ROI forms a continuous area within the image.By employing this method, researchers aim to mitigate the problem of scattered selected pixels and achieve a more cohesive and continuous representation of the ROI in medical images. This approach enhances the accuracy and reliability of subsequent image processing and analysis tasks, to more effective and precise medical diagnostics and research.

4.2 Image segmentation using deep learning:

Deep learning-based networks have achieved remarkable progress in image segmentation in recent years, with UNet standing out as one of the most prominent architectures. UNet operates on an encoding-decoding framework and has proven effective in segmenting medical images. One of its key strengths lies in its ability to capture rich spatial information through low-level feature maps, which focus on organ boundaries, and high-level feature maps, which highlight organ locations.

UNet leverages skip connections to merge the high-level semantic features obtained by a decoder with the low-level semantic features obtained by an encoder at corresponding scales. However, to address the challenge of fusing dissimilar features from different-scale feature maps in skip connections, UNet++ was introduced. UNet++ enhances the network structure by incorporating nested and dense skip connections to bridge the semantic gap between the encoder and decoder. Despite its strong performance, UNet++ still faces limitations in utilizing information from multiple scales effectively, leading to the loss of detailed features during the up-sampling and downsampling processes.

In contrast, UNet3+ represents a departure from traditional U-shaped network structures by redesigning the interconnections between encoders and decoders to capture fine- and coarse-grained semantics across the full scale. Additionally, UNet3+ employs a hybrid loss function and full-scale supervision to enhance contour segmentation. Consequently, UNet3+ achieves more accurate image segmentation compared to other U-shaped network architectures. Moreover, UNet3+ boasts computational efficiency, requiring fewer parameters for calculation, which reduces computation overhead.

Therefore, applying the UNet3+ model to the segmentation of Regions of

Interest (ROIs) in medical images promises to yield more precise segmentation results compared to traditional methods. This advancement holds significant potential for improving medical image analysis and diagnostic accuracy.

4.3 Proposed Method:

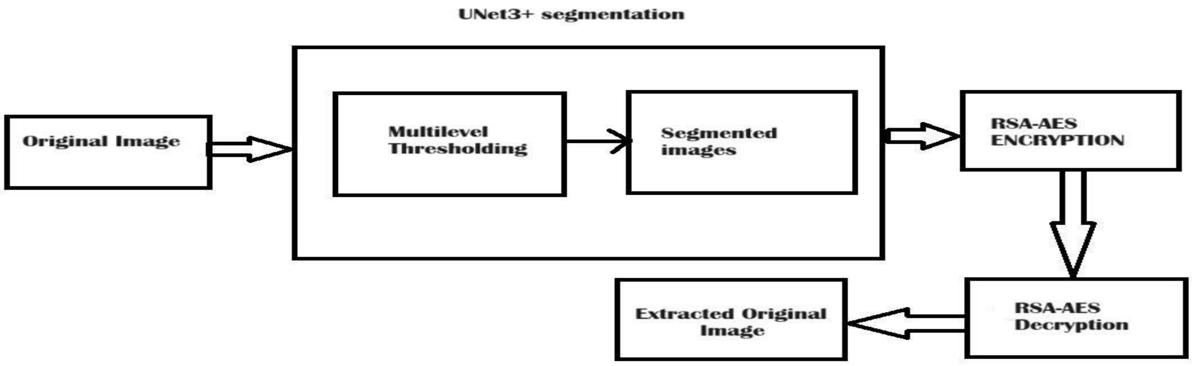

Fig 4.1 Flowchart elaborating the procedure of the proposed method

Here original image refers to the color image or greyscal greyscale image. The original image converted into the grey scale image Firstly and this image is segmented into several parts by unet3+ segmentation This Unet3+ segmentation mainly performs multilevel thresholding. Multilevel thresholding is a technique used in image processing to segment an image into multiple regions based on intensity levels. Instead of a single threshold value, multilevel thresholding involves determining several threshold values to partition the image into distinct segments with different intensity ranges.

Imagine you have a grayscale image where different regions represent various objects or features of interest, each with different intensity levels. Multilevel thresholding helps in segmenting these regions accurately by identifying thresholds that separate different intensity ranges.

Here's a simplified explanation of how multilevel thresholding works:

1. Intensity Distribution: First, the intensity distribution of the image is analyzed to understand the range of intensity values present.

2. Threshold Selection: Multiple threshold values are then chosen based on the intensity distribution. These thresholds divide the intensity range into several intervals.

3. Segmentation: The image is segmented into multiple regions based on these threshold values. Pixels with intensity values falling within each interval are assigned to the corresponding segment.

4. Region Refinement: Finally, post-processing techniques may be applied to refine the segmented regions, such as noise removal or merging adjacent regions with similar characteristics.

Overall, multilevel thresholding allows for more nuanced segmentation of

images, particularly in scenarios where objects or features exhibit varying intensity levels. It's commonly used in applications such as medical image analysis, remote sensing, and computer vision tasks to extract meaningful information from images.

By this way multilevel thresholding is performed after that reversible data hiding is carried out by the rsa and aes algorithm.In this process, RSA (Rivest-Shamir-Adleman) and AES (Advanced Encryption Standard) are cryptographic algorithms used to secure data, including images, by encrypting and decrypting them. Both algorithms play crucial roles in ensuring data confidentiality and integrity in various applications.

RSA Algorithm: RSA is a widely used asymmetric encryption algorithm. This algorithm uses a public-private key pair, where the public key is used for encryption, and the private key is used for decryption. Here's how it works:

1.Key Generation: First, the recipient generates a public-private key pair. The public key is shared with one who wants to share encrypted data, while the private key is kept as secret.

2. Encryption: To encrypt an image using RSA, the sender retrieves the recipient's public key. Each pixel value in the image is treated as a number, and the encryption process involves raising each pixel value to the power of the recipient's public key modulus and taking the result modulo the public key exponent.

3. Decryption: The recipient uses their private key to decrypt the encrypted image. Each encrypted pixel value is raised to the power of the private key modulus and taken modulo the private key exponent. RSA offers strong security due to the computational difficulty of factoring large prime numbers, which are used in key generation. However, it is relatively slow compared to symmetric encryption algorithms like AES. AES Algorithm: AES is a symmetric encryption algorithm widely adopted for its efficiency and security. Unlike RSA, AES uses the same key for both encryption and decryption. Here's how it works:

1. Key Expansion: AES requires a key of fixed length (128, 192, or 256 bits). If the provided key is shorter, it undergoes key expansion to generate a key schedule for encryption and decryption.

2. Substitution: AES operates on blocks of data, typically 128 bits in size. During encryption, each byte in the block undergoes a substitution process using a substitution box (S-box) to create confusion.

3. Permutation: The data undergoes a permutation process where rows are shifted cyclically and columns are mixed to create diffusion.

4.Rounds: AES operates in multiple rounds, with the number of rounds determined by the key size. Each round consists of substitution, permutation, and key mixing operations.

5.Final Round: The final round excludes the permutation step and concludes with the output of the encrypted data.

AES offers high-speed encryption and decryption, making it ideal for securing large amounts of data, including images. It provides strong security against various cryptographic attacks when used with a sufficiently long key. Like this way an original image can be segmented and after that reversible data hiding is done by encryption and decryption process.

CHAPTER 5

SOFTWARE DESCRIPTION

5.1 Tools used in project:

While implementing reversible data hiding-based contrast enhancement with multi-group stretching for the Region of Interest (ROI) of medical images these are the various tools used:

5.1.1 MATLAB: MATLAB is a powerful platform designed for numerical computing, data analysis, and visualization. It provides a comprehensive set of tools and functions suitable for developing algorithms and processing medical images.

***5.1.2 Deep Learning Toolbox Description*:** The Deep Learning Toolbox within MATLAB is specifically designed for tasks related to deep learning. It offers tools for designing, training, and deploying deep neural networks. In this project, the Deep Learning Toolbox will be utilized for implementing the deep learning-based segmentation model to extract the ROI from medical images.

5.1.3 MATLAB Files (M-files): MATLAB files, also known as M-files, contain code written in the MATLAB programming language. These files are essential for implementing algorithms and conducting computations within the MATLAB environment. M-files will be created to define the steps involved in reversible data hiding, contrast enhancement, and multi-group stretching for the ROI.

1. **M-Files:** M-files, specifically tailored for MATLAB, will be used to implement various algorithms and computations required for the data hiding and image enhancement processes. These files will contain the logic and instructions necessary for performing reversible data hiding, contrast enhancement, and stretching operations.
2. **MATLAB Tool:** MATLAB provides a range of tools and utilities to aid in the development, debugging, and analysis of MATLAB code.

These tools include the MATLAB Editor for writing and editing scripts, the Command Window for executing commands interactively, and the Workspace for managing variables and data.

3. **MATLAB Working Environment:** The MATLAB working environment encompasses the interface and settings within MATLAB where users interact with code, data, and visualizations. It includes features such as the Command Window, Current Folder browser, Editor, and various toolbars for accessing functions and settings.
4. **Python:** Python is a versatile programming language known for its simplicity and readability. It offers a rich ecosystem of libraries and frameworks, including NumPy, Pandas, and TensorFlow. While MATLAB will primarily be used for image processing tasks, Python may be employed for specific aspects of the implementation, such as certain data manipulation or visualization tasks.

By leveraging the capabilities of MATLAB, including its Deep Learning Toolbox, and potentially incorporating Python for additional functionalities, the project aims to develop a comprehensive solution for reversible data hiding-based contrast enhancement with multi-group stretching for the ROI of medical images.

5.2 Steps followed in implementing the project:

For implementing the project RDHCE using MATLAB and Python, the following steps can be followed:

5.2.1 Preprocessing Medical Images:

- Load medical images into MATLAB or Python.
- Perform pre-processing tasks such as resizing, normalization, and noise reduction to prepare images for further analysis.

5.2.2 ROI Detection:

- Utilize image processing techniques or deep learning models (implemented in MATLAB with the Deep Learning Toolbox or in Python using libraries like TensorFlow or PyTorch) to detect the Region of Interest (ROI) in medical images.

5.2.3 Data Hiding:

- Implement reversible data hiding algorithms using MATLAB M- files or Python scripts.
- Embed additional data (e.g., watermarks or annotations) into the ROI while ensuring reversibility.

5.2.4 Contrast Enhancement:

- Apply contrast enhancement techniques (e.g., histogram equalization, contrast stretching) to the ROI to improve its visual quality and highlight important details.

5.2.5 Multi-group Stretching:

Implement multi-group stretching algorithms to further enhance the contrast and adjust the dynamic range of pixel values within the ROI, improving its overall appearance and readability.

5.2.6 Evaluation and Validation:

- Evaluate the effectiveness of the implemented algorithms using quantitative metrics (e.g., PSNR, SSIM) and qualitative assessment through visual inspection.
- Validate results to ensure data hiding and contrast enhancement are reversible and do not degrade the diagnostic quality of medical images.

5.2.7 Optimization and Refinement:

- Fine-tune parameters and algorithms based on feedback from evaluation and validation.
- Optimize code for efficiency and scalability, considering factors such as processing speed and memory usage.

5.3 Features of MATLAB:

MATLAB, renowned for its matrix-based computation, offers a robust environment for numerical tasks. Its extensive array of built-in functions facilitates operations across various fields like linear algebra, signal processing, and statistics.

Within MATLAB's interactive interface lies a command-line and graphical interface, enabling seamless execution of commands, script development, and code debugging. The immediate feedback in the command window facilitates swift data exploration and algorithm testing.

A hallmark of MATLAB is its vast library of functions and toolboxes, spanning domains such as image processing, control systems, and machine learning. These resources empower users to tackle complex analyses without the need for extensive custom coding.

Data visualization capabilities in MATLAB are unmatched, featuring versatile plotting functions, 2D/3D graphics, and interactive visualization tools. Users can create compelling visual representations of their data to effectively communicate insights.

MATLAB's compatibility with external languages like C, C++, Java, and Python fosters interoperability, allowing users to seamlessly integrate external libraries and functions into their MATLAB workflows.

The integrated development environment (IDE) within MATLAB offers a comprehensive suite of features including a code editor, debugger, profiler, and version control integration. This facilitates efficient code navigation, analysis, and project management, streamlining the software development process.

Support for parallel computing and GPU acceleration in MATLAB enables users to leverage the computational power of multicore processors and GPUs for faster execution of computationally intensive tasks.

MATLAB facilitates easy deployment of applications as standalone executables, web apps, or shared libraries, ensuring seamless distribution and execution across diverse platforms.

Extensive documentation, tutorials, examples, and online resources provided by MATLAB empower users to learn and master the platform. Additionally, the active MATLAB community offers forums and discussion groups for collaboration and knowledge sharing among users worldwide.

5.4 Applications of MATLAB:

- MATLAB serves as a cornerstone in engineering and scientific research, offering a versatile platform for modelling, simulating, and analysing intricate systems across diverse fields like aerospace, biomedical, electrical, mechanical engineering, as well as physics, chemistry, and environmental science.
- In the realm of image and signal processing, MATLAB reigns supreme, facilitating tasks such as image restoration, enhancement, segmentation, object detection, and various audio processing endeavours like speech recognition and communication systems.
- For the design, analysis, and control of dynamic systems, including control systems, robotics, mechatronics, and autonomous vehicles, MATLAB provides indispensable tools. Its capabilities span modelling, simulation, and optimization, aiding in the development of cutting-edge control systems and robotics algorithms.
- In the realm of machine learning and data analytics, MATLAB offers a comprehensive suite of tools encompassing supervised and unsupervised learning, reinforcement learning, deep learning, and predictive analytics. Its applications range from classification and regression to clustering, anomaly detection, and pattern recognition.
- In finance and economics, MATLAB finds extensive utility for quantitative analysis, financial modelling, risk management, portfolio optimization, and algorithmic trading. Its capabilities extend to time

series analysis, Monte Carlo simulation, and financial instrument pricing, among others.

- Within educational institutions, MATLAB serves as a vital educational tool, facilitating hands-on learning experiences in mathematics, engineering,
computer science, and data science. Its intuitive interface and rich library of functions provide students with a conducive environment to explore concepts, solve problems, and conduct experiments.
- In essence, MATLAB stands as an indispensable ally for researchers, engineers, scientists, and educators worldwide, offering an intuitive interface, extensive library of functions, and a rich ecosystem conducive to innovation and discovery.

5.5 DEEP LEARNING TOOLBOX DESCRIPTION:

The Deep Learning Toolbox is a comprehensive software package provided by MathWorks as part of the MATLAB environment, designed to facilitate deep learning research, development, and deployment. It offers a rich set of tools, algorithms, and functions for designing, training, visualizing, and deploying deep neural networks (DNNs) for various applications.

Key Features of Deep Learning Toolbox:

Deep Neural Network Architectures: Deep Learning Toolbox provides support for building and training various types of deep neural network architectures, including convolutional neural networks (CNNs), recurrent neural networks, short-term memory networks, and generative adversarial networks (GANs). Users can create custom network architectures using high-level building blocks or pre-trained models from the MATLAB Model Zoo.

Training and Optimization: The toolbox offers flexible and scalable tools for training deep neural networks on large datasets, including support for parallel computing, GPU acceleration, and distributed training. Users can customize training options such as optimization algorithms, learning rates, batch sizes, and regularization techniques to achieve optimal performance and convergence.

Transfer Learning: Deep Learning Toolbox supports transfer learning, a technique that leverages pre-trained neural network models to accelerate training and improve performance on new tasks or datasets. Users can fine-tune pre-trained models on domain-specific data or extract features from intermediate layers for downstream tasks such as classification, object detection, or image segmentation.

Data Augmentation: The toolbox provides functions for data augmentation, a technique that artificially increases the diversity and size of training datasets by applying random transformations such as rotation, translation, scaling, and flipping to input images. Data augmentation helps improve model generalization and robustness by exposing the network to a wider range of variations and scenarios.

Visualization and Interpretation: Deep Learning Toolbox offers tools for visualizing and interpreting deep neural network models, including layer activations, feature maps, gradients, and training progress. Users can visualize the learned representations and understand how the network processes input data, making it easier to diagnose performance issues, debug models, and gain insights into network behaviour.

Model Deployment: The toolbox enables users to deploy trained deep neural network models to various target platforms and environments, including desktop, embedded systems, and cloud services. Users can generate standalone executable files, deployable archives, or MATLAB code for integrating trained models into applications, software systems, or production pipelines.

Integration with MATLAB Ecosystem: Deep Learning Toolbox seamlessly integrates with other MATLAB toolboxes and functions, allowing users to leverage MATLAB's extensive ecosystem for data preprocessing, feature engineering, visualization, and analysis. Users can combine deep learning with traditional machine learning techniques, signal processing algorithms, and domain-specific toolboxes to solve complex problems more effectively.

5.6 Applications of Deep Learning Toolbox:

Computer Vision: Deep Learning Toolbox is widely used in computer vision applications such as image classification, object detection, semantic segmentation, image recognition, and scene understanding. It provides pre-trained models and transfer learning capabilities for tasks like ImageNet classification, COCO object detection, and Pascal VOC segmentation.

Natural Language Processing: The toolbox supports natural language processing (NLP) tasks such as text classification, sentiment analysis, named entity recognition, and language translation. Users can build and train deep learning models for processing text data using techniques like recurrent neural networks (RNNs) and transformer architectures.

Speech and Audio Processing: Deep Learning Toolbox offers tools for speech recognition, speech synthesis, speaker identification, and audio classification tasks. Users can train deep neural networks on speech and audio datasets to develop accurate and robust models for various applications in speech processing and audio analysis.

Healthcare and Biomedical Imaging: The toolbox is used in healthcare and biomedical imaging applications for medical image analysis, disease diagnosis, and treatment planning. It enables researchers and clinicians to develop deep learning models for tasks such as MRI segmentation, CT image reconstruction, histopathology analysis, and genomics data analysis.

Autonomous Systems and Robotics: Deep Learning Toolbox is employed in autonomous systems and robotics applications for perception, localization, mapping, and navigation. It enables developers to build deep learning models for object detection, obstacle avoidance, path planning, and gesture recognition in autonomous vehicles, drones, and robotic systems.

Finance and Economics: The toolbox is utilized in finance and economics for time series forecasting, risk management, algorithmic trading, and financial modelling. It allows analysts and traders to develop deep learning models for predicting stock prices, portfolio.

In summary, the Deep Learning Toolbox provides a comprehensive set of tools and functionalities for developing, training, and deploying deep neural networks for various applications across different domains.

Its integration with the MATLAB ecosystem and support for advanced deep learning techniques make it a valuable asset for researchers, engineers, and practitioners working in the field of artificial intelligence and machine learning.

5.7 MATLAB Working Environment:

The MATLAB working environment refers to the interactive computing environment provided by MATLAB for developing, executing, and debugging MATLAB code and applications. The MATLAB working environment includes various components and features that enable users to write code, analyse data, visualize results, and interact with MATLAB tools and functions. Below are some key aspects of the MATLAB working environment:

Command Window: The Command Window is the primary interface for interacting with MATLAB, allowing users to execute MATLAB commands, run scripts, and evaluate expressions interactively. Users can type commands directly into the Command Window and receive immediate feedback, making it easy to explore MATLAB functionality and test code snippets.

Editor: The Editor is a built-in code editor in MATLAB for writing, editing, and debugging MATLAB code and scripts. It provides syntax highlighting, code folding, automatic indentation, and other features to enhance code readability and productivity. The Editor also includes debugging tools such as breakpoints, step-through execution, and variable inspection for diagnosing and fixing errors in MATLAB code.

Workspace: The Workspace is a graphical interface in MATLAB that displays the current variables, arrays, and data objects in memory. Users can view variable values, inspect data properties, and perform operations on workspace variables using interactive tools. The Workspace enables users to manage data, track variable changes, and debug code more effectively.

Current Folder: The Current Folder window displays the contents of the current working directory in MATLAB, including files, folders, and MATLAB scripts. Users can navigate the directory structure, open files, and run scripts directly from the Current Folder window. The Current Folder window helps users organize files, manage project resources, and access MATLAB functions and toolboxes.

Command History: The Command History window records the history of MATLAB commands and statements executed during the current MATLAB session. Users can view previous commands, repeat commands, and search command history using interactive tools. The Command History window facilitates command recall, exploration of command sequences, and documentation of MATLAB workflows.

Figure Windows: Figure Windows are graphical windows in MATLAB used for visualizing data, plotting graphs, and displaying images. Users can create multiple Figure Windows to view and compare different plots or visualizations simultaneously. Figure Windows support interactive tools for zooming, panning, rotating, and annotating plots, enhancing data exploration and analysis.

Toolbox Explorer: The Toolbox Explorer is a graphical interface in MATLAB that provides access to MATLAB toolboxes, functions, and documentation. Users can browse toolbox contents, search for functions, and access documentation and examples using interactive tools. The Toolbox Explorer helps users discover and utilize MATLAB functionality more efficiently.

Online Help: MATLAB provides comprehensive online help documentation, tutorials, and examples to assist users in learning MATLAB and solving technical challenges. Users can access online help resources directly from the

MATLAB interface, including documentation for functions, toolboxes, and programming concepts. Online Help enables users to find answers, learn new features, and troubleshoot issues in MATLAB.

Preferences and Settings: MATLAB allows users to customize their working environment by configuring preferences and settings according to their preferences and workflow. Users can adjust settings for syntax highlighting, code completion, keyboard shortcuts, and editor behaviour to optimize their MATLAB experience. Preferences and settings enable users to tailor MATLAB to their specific needs and preferences.

In summary, the MATLAB working environment provides a powerful and intuitive platform for developing, executing, and debugging MATLAB code and applications. Its interactive features, graphical tools, and integrated documentation support efficient coding, data analysis, visualization, and exploration of MATLAB functionality, making it a preferred choice for engineers, scientists, researchers, and students worldwide.

CHAPTER 6

SIMULATION RESULTS

This chapter shows the results obtained after performing the simulation using MATLab software.The following image is the input color image before performing the simulation.

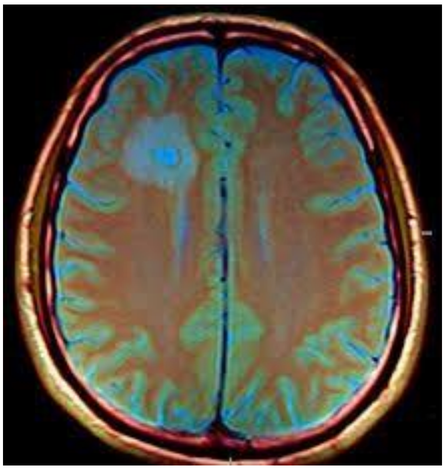

Figure 6.1 Input image

After performing the segmentation using Unet3+ networking model the following segmentation levels obtained.

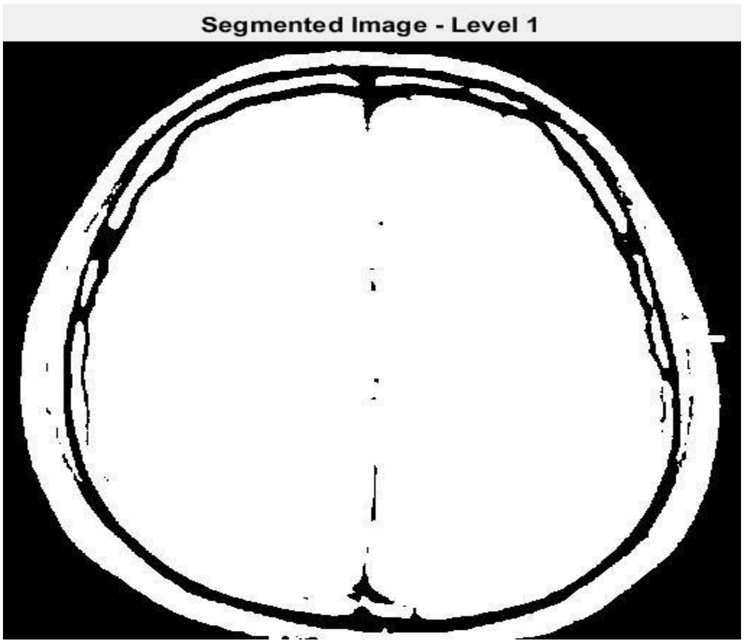

Figure 6.2 Segmentation level1

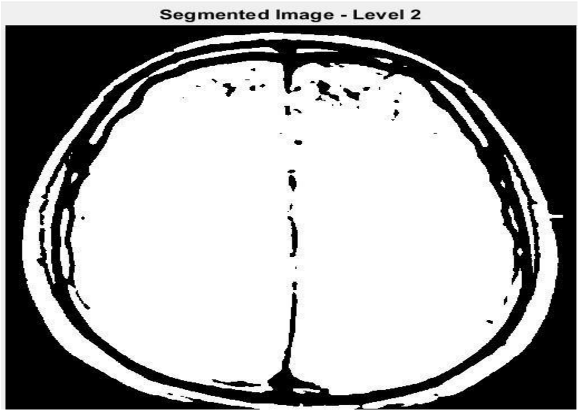

Figure 6.3 Segmentation level2

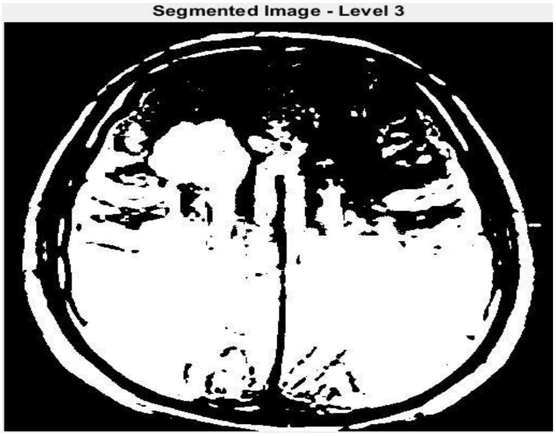

Figure 6.4 Segmentation level3

Figure 6.5 Segmentation level4

Figure 6.6 Segmentation level5

After performing the unet3+ segmentation the input image is segmented into 5 levels as shown in the above figures.

RDHCE is performed by rsa-aes algorithm as shown in the below figures.

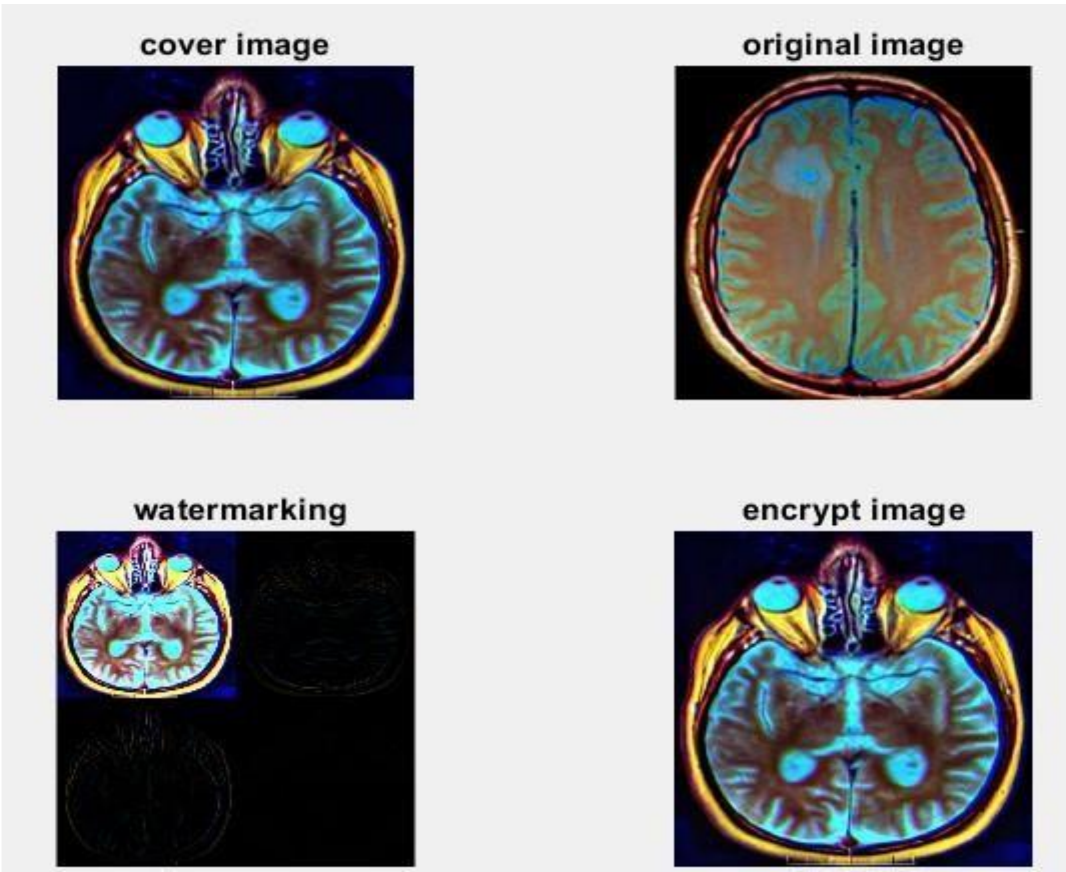

Figure 6.7 Reversible data hiding encryption process

In Figure 6.7 the original image is encryted in cover image and finally it wont be accessed by anyone.It got encrypted within another image.Here watermarking is done to hide the original image information.

While retreiving the original image by giving the watermarked image shown in figure 6.8 as an input to the receiver the original image can be retrieved.

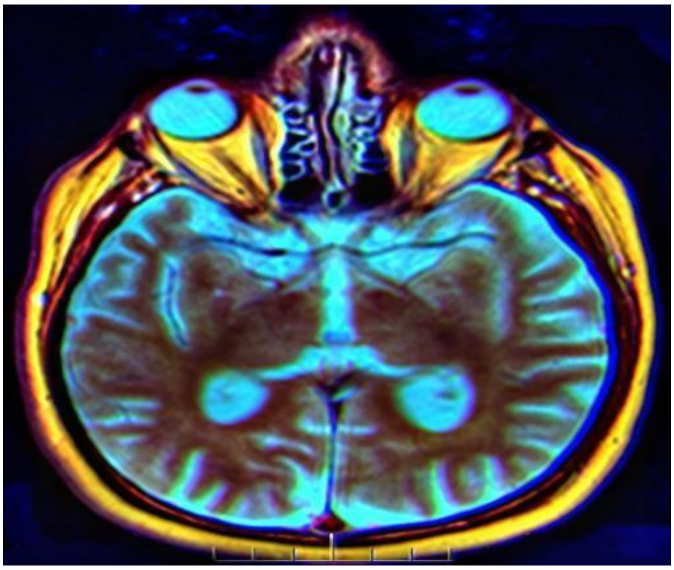

Figure 6.8 Extracted Watermarked image

The output original image obtained is shown in the below figure 6.9. The final enhanced original image is obtained by rsa-aes decryption.

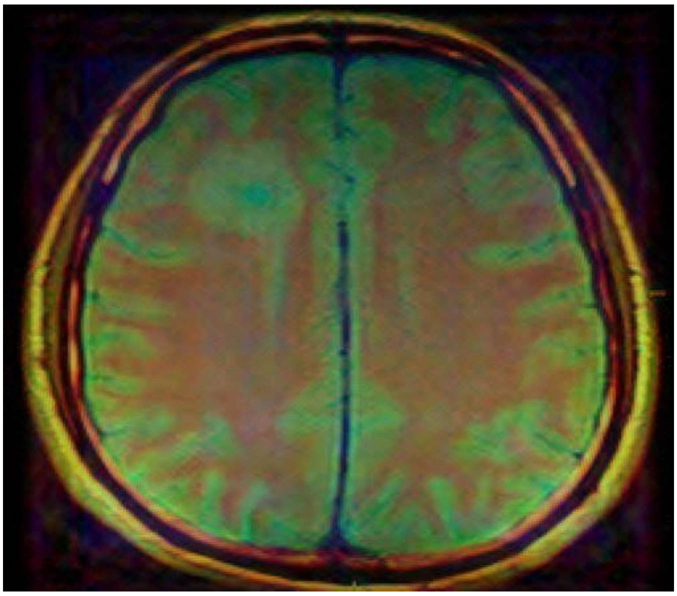

Figure 6.9 Extracted original image

Peak signal to noise ratio:

Peak Signal-to-Noise Ratio (PSNR) in digital image processing provides a clear measure of how much a reconstructed or compressed image deviates from the original, in terms of both signal power and introduced noise. Think of it as a quality score, where higher values indicate better fidelity.

Imagine you have an original image and a compressed version of it. PSNR tells you, in straightforward terms, how similar they are. It's like comparing two pieces of music: one in pristine quality and the other after compression. PSNR quantifies how much of the original "music" is lost or distorted during compression.

Here's how it works: PSNR calculates the ratio between the maximum possible power of the original image (the signal) and the average power of the noise introduced during compression (the distortion). The result is expressed in decibels (dB), making it easy to understand – higher dB means less distortion and better image fidelity.

So, when you hear about PSNR in digital image processing, think of it as a reliable gauge of how faithfully an image has been preserved through compression or reconstruction, with higher values indicating a closer resemblance to the original.

The formula for Peak Signal to Noise Ratio is:

Peak signal to noise ratio =

10*log10(vmax^2/Mean square error)

Where:

- Vmax is the maximum possible pixel value of the image (for example, 255 for an 8-bit image).
- Mean square error between the original and reconstructed/encrpted images. It's calculated by averaging the squared differences between corresponding pixels in the two images.

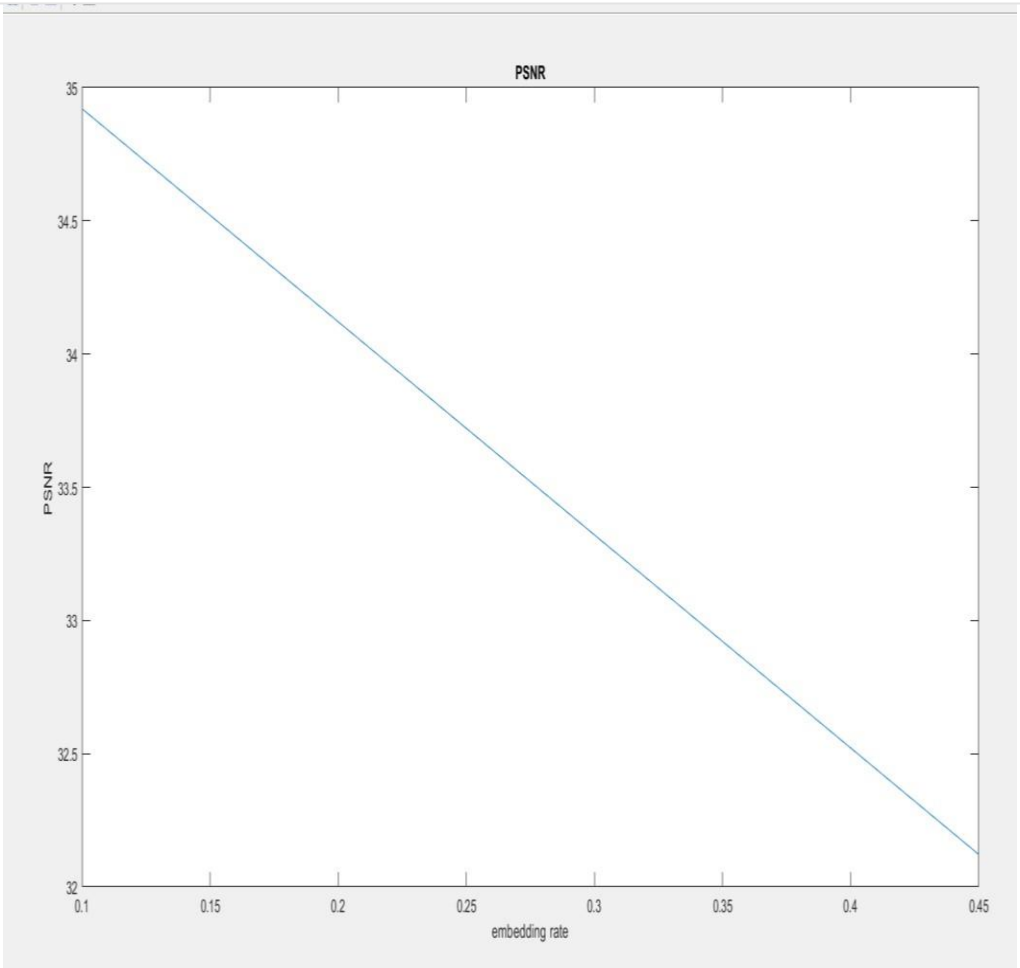

Figure 6.10 PSNR vs Embedding rate

Comparison:

By comparing the PSNR factor with the existed methods the PSNR factor is increased by 1.02%.

Image set	**PSNR**	**RCE**
1.Brain	35	0.59
2.Kidney	33	0.58

Table 6.1 Comparison table

This is the comparison table which shows the comparison of psnr and rce values for brain and kidney.

Peak Signal-to-Noise Ratio (PSNR) and Relative Contrast Enhancement (RCE) are both metrics used in medical imaging, particularly in analyzing images of organs like the brain and kidneys.

PSNR measures the quality of an image reconstruction or compression by comparing the original image with the reconstructed/compressed version. It quantifies how much noise or distortion is introduced during the reconstruction or compression process.

RCE assesses the enhancement of contrast between different regions or structures within an image.It measures how much the contrast between different areas of the image has been improved after a specific image enhancement technique.

while PSNR focuses on overall fidelity and noise levels between the original and processed images, RCE specifically evaluates the improvement in contrast between different regions or structures within the image after enhancement techniques are applied. Both metrics serve different purposes in assessing image quality and enhancement in medical imaging.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 CONCLUSION

The method starts with segmenting the Region of Interest (ROI) within the medical images using an advanced deep learning-based network Then, it divides the histogram of the ROI into different functional intervals automatically.

These intervals are grouped and processed separately to stretch the histogram, effectively expanding the dynamic range of the image. Experimental results demonstrate the versatility of the proposed method across various medical images with different histogram distributions. Compared to similar methods in previous studies, the proposed method significantly increases the maximum embedding capacity within the ROI by approximately 3.5 times.
Furthermore, it enhances the Relative Contrast Enhancement (RCE) value by at least 5% when compared with existing state-of-the-art methods.

7.2 FUTURE SCOPE

However, it's noted that the proposed method is tailored for grayscale medical images and isn't directly applicable to color images.Future research will concentrate on refining the embedding strategy to accommodate the unique characteristics and correlations among the three color channels of medical images, thus enabling the method's effective application to color medical imagery.

In essence, the paper presents an innovative approach that significantly boosts both the capacity and quality of hidden data within medical images, with a specific focus on grayscale images. Yet, it also highlights the need for further exploration to adapt the method for color medical images in future studies.

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