EDGE DETECTION FOR BRAIN TISSUE SEGMENTATION IN MR IMAGE

A Thesis submitted to Gujarat Technological University

for the Award of

Doctor of Philosophy

in

Biomedical Engineering

by

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(189999918007)

under supervision of

Dr. Tejas Vinodchandra Shah

GUJARAT TECHNOLOGICAL UNIVERSITY

AHMEDABAD

March-2024

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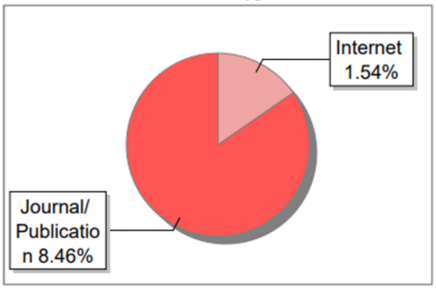

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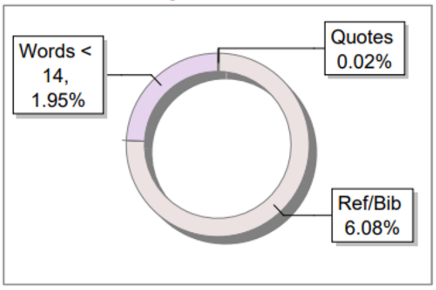

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ABSTRACT

EDGES are a crucial aspect of object and image representation and analysis. They separate an object from its background, highlighting the object's surface characteristics and defining its inter-object boundaries and internal textures. In semi-automatic or fully automatic image analysis and understanding, edges play a significant role in the detection and representation process. They serve as a prominent characteristic feature for representing the shape of an object.

Magnetic resonance imaging (MRI) or nuclear magnetic resonance imaging (NMRI) is primarily a medical imaging technique used in radiology to visualize the internal structure of the body. MRI provides a much greater contrast between different soft tissues of the body. This ability makes it useful for neurological, musculoskeletal, cardiovascular, and oncological imaging. Human brain matter tissues can be categorized as White matter (WM), Gray matter (GM), and Cerebrospinal fluid (CSF). Most of the brain structures are anatomically defined by the edges of these tissues. Detection of these edges is an important step for quantitative analysis of the brain and its anatomical structures. It is also an important step for the detection of various pathological conditions affecting brain parenchyma. It is also used for surgical planning, simulation, and three-dimensional visualization to diagnose and detect abnormalities. It is also useful in the study of brain development and human aging. As a result of low contrast, various sources of noise, partial volume effects, structural variations, and various types of artifacts the edge detection process of MRI images of the brain is non-trivial.

ABSTRACT

Starting from the basic definition of the edge, the phenomenon of the appearance of edges in the image, different models used to model the edge like step, ramp, line, and roof edge models are presented. The well-known traditional edge detectors like Roberts Edge Detector, Prewitt Edge Detector, Sobel - Feldman Edge Detector as well state of art and cutting-edge edge detectors like Holistically-Nested Edge Detector, Richer Convolutional Features Edge Detector, Bi-Directional Cascade Network for Perceptual Edge Detector and Dense Extreme Inception Network Edge Detector are implemented and analyzed.

MRI images always contain a significant amount of noise caused by operator performance, equipment, and the environment. This noise can lead to major inaccuracies in the edge detection process and hence in segmentation results. We conduct research in measuring the performance of Edge Detectors for edge detection in different noise levels for MRI images. To validate the accuracy and robustness of these Edge Detectors we carried out experiments on MRI brain scans. The performance of the edge detectors is analyzed by different quantitative measures. These quantitative measures like accuracy and F measure. As a result of the increasing amount of noise in the MRI image, the performance of the edge detector degrades. The noise in the image causes spurious edges and results in a decrease in the accuracy of the edge detector. We proposed an edge detector with the ability to withstand the increasing amount of noise in the MRI image. We also proposed one variation of the proposed method with a spatial variation edge detector to improve the accuracy of the edge detector in the presence of noise.

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Parmar Ghanshyam Dalsukhlal

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Nomenclature

Acronyms / Abbreviations

BCN Bi-directional Cascade Network

BDCN Bi-Directional Cascade Network

CAD Computer-Aided Diagnosis

CSF Cerebrospinal fluid

CT Computed Tomography

DexiNed Dense Extreme Inception Network

DWI Diffusion-weighted Imaging

ELM Extreme Learning Machines

fMRI Functional Magnetic Resonance Imaging

FN False Negatives

FP False Positives

GM Gray Matter

HED Holistically-Nested Edge Detector

MRI Magnetic Resonance Imaging

MR Magnetic Resonance

MRS Magnetic Resonance Spectroscopy

NMR	Nuclear Magnetic Resonance
PET	Positron Emission Tomography
RCF-ED	Richer Convolutional Features Edge Detector
RCF	Richer Convolutional Features
RFI	Radio Frequency Interference
RF	Radio Frequency
RNN	Recurrent Neural Networks
SBD	Simulated Brain Database
SNR	Signal-to-Noise Ratio
TN	True Negatives
TP	True Positives
WM	White Matter

Chapter 1

Introduction

1.1 Magnetic Resonance Imaging

The development of magnetic resonance imaging (MRI) as a medical imaging modality has a rich history. The foundation of MRI lies in the discovery of nuclear magnetic resonance (NMR), which was first described by Isidor Rabi in the 1930s. NMR involves the interaction of atomic nuclei with magnetic fields, and it is the physical phenomenon upon which MRI is based [40]. In 1946, Felix Bloch and Edward Purcell independently conducted groundbreaking experiments that demonstrated the principles of nuclear magnetic resonance. Their work laid the foundation for MRI. For their contributions, they were awarded the Nobel Prize in Physics in 1952 [3, 39]. The first MRI images of a human were produced in 1973 by Paul Lauterbur, who used magnetic field gradients to spatially encode the NMR signals. He is often credited with the development of MRI as an imaging technique [23]. Echo-Planar Imaging(EPI), a fast imaging technique used in MRI, was introduced by Peter Mansfield and his colleagues in 1977. EPI dramatically reduced imaging time and opened the door to functional MRI (fMRI) and real-time imaging [31]. The first clinical MRI scanners became available in the early 1980s. These early MRI machines were relatively low field and low resolution compared to modern systems. Nevertheless, they were instrumental in advancing medical diagnosis. In the early 1990s, scientists like Seiji Ogawa made significant contributions to the development of functional MRI (fMRI). fMRI allows researchers to study brain function by detecting changes in blood flow and oxygenation [34]. The development of diffusion-weighted imaging, which is now widely used in the assessment of stroke and other neurological conditions, can be attributed to Paul Lauterbur and Ken Kwong in the 1980s [24]. Raymond Damadian is credited with the first use of Magnetic Resonance Spectroscopy (MRS) to detect diseases like cancer. His work laid the groundwork for using MRI not only for anatomical imaging but also for chemical and metabolic information [11].Progress in superconducting magnet technology, particularly high-field magnets, has allowed for higher resolution and more detailed imaging in MRI. MRI is a continually evolving field, with ongoing research and development in various areas, including contrast agents, image acquisition techniques, and clinical applications. The field of MRI has seen significant advances since its inception, making it a critical tool in medical diagnosis and research today. Researchers and engineers continue to push the boundaries of what MRI can achieve.

1.2 Magnetic Resonance Imaging for Human Brain Understanding

Magnetic Resonance Imaging (MRI) is of paramount importance in brain imaging. MRI is a non-invasive imaging technique, which means it doesn't require the use of ionizing radiation (as in X-rays or CT scans) or invasive procedures. This is particularly advantageous when imaging the delicate and vital organ like the brain. MRI provides excellent soft tissue contrast, allowing for clear visualization of different brain structures and abnormalities. This is crucial for diagnosing various neurological conditions, as the brain is composed of different tissues with varying properties. MRI allows imaging in multiple planes (axial, coronal, sagittal), which is important in the assessment of brain structures from different perspectives and can aid in identifying the location and extent of lesions or abnormalities.

Functional MRI (fMRI) is a specialized MRI technique used to study brain function by detecting changes in blood flow and oxygenation. It is invaluable for research and clinical applications, such as mapping brain regions responsible for specific functions and studying brain disorders. DWI is used to assess the diffusion of water molecules in brain tissue. It is vital in the early detection of acute stroke, as changes in diffusion can indicate areas of ischemia. MRS allows for the assessment of brain metabolites and provides information about the biochemical composition of brain tissue. It is used to diagnose and monitor conditions like brain tumors and metabolic disorders. MRI is an essential tool for detecting various brain conditions, including tumors, vascular abnormalities, multiple sclerosis, traumatic brain injury, and neurodegenerative diseases such as Alzheimer's and Parkinson's disease. It aids in early diagnosis and treatment planning. In some cases, MRI can be used during neurosurgery to provide real-time images of the brain, helping surgeons navigate and precisely target specific areas. MRI allows for the monitoring of changes in the brain over time. This is valuable for tracking the progression of neurodegenerative diseases and the effects of treatments. MRI is indispensable in neuroscience research, helping scientists understand brain function, connectivity, and structural changes associated with various conditions. It has been instrumental in advancing our knowledge of the brain. MRI is a non-invasive and generally comfortable imaging modality, which is particularly important when dealing with patients who may be sensitive to other imaging techniques or those who require repeated scans for monitoring purposes. MRI plays a critical role in brain imaging due to its ability to provide detailed and multi-dimensional images with excellent soft tissue contrast, its non-invasiveness, and its wide range of specialized techniques for functional and metabolic assessments. It has revolutionized the diagnosis, treatment, and research related to neurological conditions and brain function [19].

1.3 Noise in MR images of Human Brain

Noise in magnetic resonance imaging (MRI) refers to random variations in pixel intensity or signal intensity that are not related to the underlying tissue characteristics but instead arise from various sources of interference. Understanding and mitigating noise is crucial in MRI, as it can affect image quality and diagnostic accuracy. Here are the details on the sources and types of noise in MR images.

1.3.1 Sources of Noise

- **Thermal Noise (Johnson-Nyquist Noise):** This type of noise arises due to the random motion of electrons in the MRI system's receiver components, such as the coils and amplifiers. It is directly proportional to temperature and bandwidth.
- **Shot Noise (Poisson Noise):** Shot noise occurs because MRI signal intensity is inherently quantized since it relies on the counting of individual radiofrequency (RF) photons. It becomes more prominent at lower signal levels.
- **Physiological Noise:** Patient motion, physiological processes (e.g., respiration and cardiac motion), and pulsatile blood flow can introduce noise into MRI images. Motion artifacts can degrade image quality and lead to noise-like features.
- **Susceptibility-Induced Artifacts:** Variations in magnetic susceptibility between different tissues can lead to phase errors in MRI data, resulting in image artifacts that can resemble noise.
- **Hardware-Related Noise:** Imperfections in the MRI hardware, including the gradient coils and radiofrequency (RF) coils, can introduce noise. These imperfections can vary from scanner to scanner and affect image quality.

- **Radiofrequency Interference (RFI):** External sources of RF radiation, such as mobile phones or electronic devices, can interfere with the MRI signal and introduce noise into the images. Proper shielding is necessary to minimize RFI.
- **Chemical Shift Artifacts:** In MR spectroscopy, differences in the chemical shift of protons in different molecules can lead to spectral misalignment, resembling noise.

1.3.2 Types of Noise

- **Gaussian Noise:** Thermal noise and shot noise typically manifest as Gaussian noise, which follows a normal distribution. Gaussian noise is characterized by a symmetrical distribution of pixel intensity variations.
- **Rician Noise:** In MRI, when the signal-to-noise ratio (SNR) is low, the noise may not be purely Gaussian but instead follows a Rician distribution. Rician noise is more prevalent in magnitude images, as opposed to complex images.
- **Salt-and-Pepper Noise:** Salt-and-pepper noise appears as random bright and dark pixels in the image, resembling salt and pepper. It is often caused by malfunctioning detector elements or data corruption.

Understanding the sources and types of noise in MRI is critical for radiologists, technologists, and researchers to interpret images accurately and improve diagnostic quality. Additionally, ongoing research and development in MRI technology aim to further reduce noise and enhance image quality [63, 17, 32].

1.4 Edge Detection for Medical Image Analysis

Edge detection plays a crucial role in the medical field due to its importance in image processing and analysis. It provides valuable information and has several applications in medical imaging and healthcare. Edge detection helps identify and delineate the boundaries of anatomical structures or regions of interest within medical images, such as organs, blood vessels, tumors, and bones. This aids in diagnosis and treatment planning. Edge detection can be used to locate the edges of tumors or lesions in medical images, facilitating early diagnosis and precise treatment. It enables radiologists to measure the size and extent of abnormalities. Detecting vessel edges and extracting their geometrical information is vital for the assessment of vascular conditions. It's used in the analysis of blood vessels, including stenosis, aneurysms, and other vascular pathologies [50].

Edge-based segmentation techniques can be applied to separate different regions of interest in medical images, making it easier to isolate and analyze specific structures within an image. The detection of edges helps in extracting features from medical images that are relevant for diagnosis and research, such as texture analysis and shape descriptors. Edge detection can enhance image quality by emphasizing important structures and reducing noise. This is particularly beneficial for improving the visibility of fine details. In applications like cardiac imaging, detecting edges can be used to monitor motion in the heart or other organs. It's essential for assessing cardiac function and detecting abnormalities.: When combining images from different modalities (e.g., MRI and CT), edge detection can aid in image registration by aligning common structures, improving the fusion of information, and facilitating multimodal analysis [8].

Edge detection techniques are used to provide real-time guidance to surgeons during procedures by highlighting relevant structures in the surgical field. Edge-based features are often used in Computer-Aided Diagnosis (CAD) systems to assist radiologists in making more accurate and consistent diagnoses, particularly in fields like radiology and pathology. Researchers use edge detection to quantify changes in medical images over time, allowing for the study of disease progression and the evaluation of treatment effectiveness. Edge detection is valuable in the monitoring and follow-up of patients, enabling the comparison of images acquired at different time points to track disease progression or treatment response. Edge detection techniques are indispensable tools in medical imaging and analysis. They contribute to the accurate diagnosis, treatment, and research of various medical conditions, enhancing the capabilities of healthcare professionals and improving patient care [64].

1.5 Overview of the Thesis

In Chapter 2, we delve into the fundamentals of edge detection, encompassing edge concepts, edge detection techniques, and the exploration of both traditional and state-of-the-art edge detectors. We also explore the intricacies associated with edge detection in MR images of the human brain, shedding light on the challenges inherent in this context. This chapter culminates in a precise problem definition, outlining the objectives of our research, and delineating the scope of the work.

Chapter 3 focuses on the methodology employed in this study. We commence with a comprehensive discussion of Monotonic and Bitonic signals, accompanied by graphical representations for better understanding. Subsequently, we delve into the intricacies of Bitonic filters. The chapter then progresses to the heart of our research, where we introduce the Proposed Bitonic edge detector, offering a detailed mathematical representation. Furthermore, we explore a structural variation of the Bitonic edge detector within the same chapter.

In Chapter 4, we turn our attention to the experimental aspects of our study. This chapter provides a detailed account of the experimental setup, focusing on the MR image dataset and the associated noise characteristics. We meticulously document the outcomes of applying both traditional edge detectors and state-of-the-art edge detectors to this dataset. The resulting images are showcased and analyzed. Additionally, we present the results of our Proposed Bitonic edge detector, complete with a discussion of its mathematical underpinnings. Furthermore, we delve into the structural variation of the Bitonic filter and its associated results, facilitating a comparative analysis with the outcomes of traditional and state-of-the-art edge detectors.

In Chapter 5, we shift our focus to the validation process of the obtained results. We explore various metrics and measures for assessing the performance of the employed edge detection techniques. The chapter includes a comprehensive presentation of the performance evaluations for both traditional edge detectors and state-of-the-art alternatives, conveyed through graphical representations. Additionally, we rigorously evaluate the performance of our Proposed Bitonic edge detector and its structural variation, the Bitonic filter. These results are discussed in detail and are subjected to a comparative analysis against the performance of traditional and state-of-the-art edge detectors.

In Chapter 6, we draw conclusions regarding the performance of edge detectors in the presence of increasing noise levels. This chapter encapsulates the key findings and insights gathered from the previous chapters, shedding light on the effectiveness of edge detection techniques under varying noise conditions. Furthermore, we explore the future scope and potential directions for further research and development in this area within the same chapter.

Chapter 2

Background and Literature Review

In this Chapter, we delve into the fundamentals of edge detection, encompassing edge concepts, edge detection techniques, and the exploration of both traditional and state-of-the-art edge detectors. We also explore the intricacies associated with edge detection in MR images of the human brain, shedding light on the challenges inherent in this context. This chapter culminates in a precise problem definition, outlining the objectives of our research, and delineating the scope of the work.

2.1 Background

2.1.1 Edge

Image is defined as the two (or three) dimensional function of intensity with respect to the spatial coordinates. These intensities are distributed over the spatial coordinates to represent any three-dimensional object or the scene. hence the physics of the object or the objects in the scene and the background causes discontinuity in the intensity distribution function. This discontinuity in the intensity level of the image is called Edge. Edge is any change of the intensity value with respect to the neighboring pixel's intensities. Higher the change results in significant edges. And, lower the change results in spurious edges. The significant edges are considered to be one of the important feature for image characteristics representation and spurious edges may represent very low intensity variation, low level texture or noise in the image. The spurious edges increases as the noise level in the image increases. Hence, the significant edges increases in the image after low-pass filtering of the image.

Edges in the image appears due to one of the three phenomena namely physical, geometrical and non-geometrical events. The image of the physical object with the background causes the edges between the object and the background. Here, the resulting edges are due to the phenomenon of physical events. The object boundary, discontinuity in the object surface and textures also appears as edges in the image. Here, the resulting edges are due to the phenomenon of geometrical events. The shadows, internal reflections and specularity also results as edges in the image. Here, the resulting edges are due to the phenomenon of non-geometrical events.

2.1.2 Edge Modeling

Edges represent one of the key characteristics of the image representing the object or scene. It is significant to identify and detect the edges in the image. As the mathematical representation of these edges involve the complexity of representation increasing with increasing number of pixels, makes the representation computationally complex in terms of representation and calculation as well practical implementation and detection. To simplify the complexities involved in representation of these edges, edges are modeled with the simplified and minimal representational and computational expenses involved. Based on the intensity profile these edges are modeled. These simplified models are step, ramp, line and roof edge model [13, 37].

A step edge model is the characterization of intensity profile of the neighboring pixels with step change in the intensities. In the figure 2.1 the one dimensional edge profile of step edge model is shown. The step edge occurs in the image as a result of sharp and significant discontinuity. This edge model represents a clean and ideal edge, which results after significant preprocessing on the obtained raw image [13, 37].

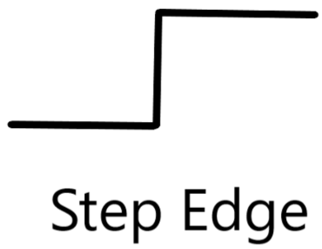

Fig. 2.1 The one Dimensional profile of the Step edge model

A ramp edge model is the characterization of intensity profile of the neighboring pixels with ramp like monotonically increasing or decreasing change in the intensities.In the figure 2.2 the one dimensional edge profile of ramp edge model is shown.The ramp edge occurs in the image as the result of blur or defocused object. This edge model represents the degree to which the discontinuity is blurred in the image [13, 37].

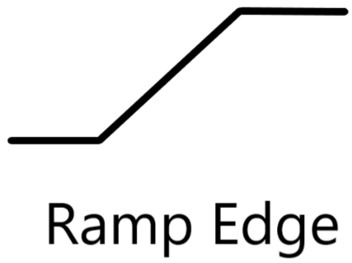

Fig. 2.2 The one Dimensional profile of the Ramp edge model

A line edge model is the characterization of intensity profile of the pixels with bumped line intensity profile with respect to their neighboring pixels.In the figure 2.3 the one dimensional edge profile of line edge model is shown. The line edge occurs in the image as the result of strip, road or ridge like objects or structures [13, 37].

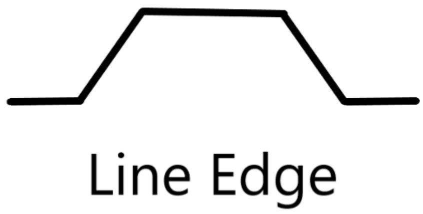

Fig. 2.3 The one Dimensional profile of the Line edge model

A roof edge model is the catheterization of intensity profile of the neighboring pixels with two conjugate ramp like monotonically increasing or decreasing with decreasing or increasing change in the intensities. In the figure 2.4 the one dimensional edge profile of roof edge model is shown. The roof edge occurs in the image as a result of pipes, digitization of line drawings, satellite images with road like structures [13].

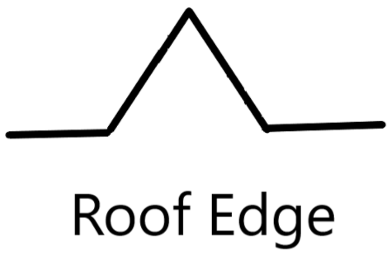

Fig. 2.4 The one Dimensional profile of the Roof edge model

In real life situations the edges will be the mixture of above-mentioned model with added with different noises and bias. The addition of noises and bias in the image cause the task of edge detection to be non-trivial [13, 37].

2.2 Edge Detector

The operator or algorithm used to detect the edge in the image is known as edge detector. In simple terms, the process to detect the edge in the image is known as edge detector. It could be as simple as a differential operation or the difference operation. Also, it could be a highly complex algorithm with machine learning and deep learning techniques. Here, we describe some of the well-known traditional edges detectors as well state of art and cutting-edge edge detectors.

2.2.1 Traditional Edge Detectors

Roberts Edge Detector

The Roberts cross-gradient operator proposed by Lawrence Roberts in 1965 [41]. It is a discrete two-dimensional differential operator used to emphasize and detect the gradient of the intensity function of image. The operator computes the gradient of an image through discrete differentiation, achieved by calculating the sum of the squares of the differences between diagonally adjacent pixels. The result of this operator corresponds either to the intensity gradient or the norm of the intensity gradient in the image. This is based on convolution of the image with two separable and integer valued horizontal and vertical operators, frequently known as masks. Given the input image $I(x, y)$ of size m by n, where $x = 1, 2 \ldots, m$ and $y = 1, 2, \ldots, n$ are horizontal and vertical indices of the image.

$$RF_x = \begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix} \tag{2.1}$$

and

$$RF_y = \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix} \tag{2.2}$$

Where RF_x and RF_y are derivative approximation in horizontal and vertical direction respectively. They are separable and integer valued small filters in horizontal and vertical directions. By convolving the $I(x, y)$ with G_x and G_y we obtain two different images with horizontal and vertical edge approximation

$$G_x = I(x, y) * RF_x \tag{2.3}$$

and

$$G_y = I(x, y) * RF_y \tag{2.4}$$

Where $*$is the convolution operator and G_x and G_y are the horizontal and vertical edge approximations respectively. The final edge image is obtained by computing the gradient approximation with equation:

$$E_R(x, y) = \sqrt{{G_x}^2 + {G_y}^2} \tag{2.5}$$

The resulting image $E_R(x, y)$ is known as Roberts Edge approximation of original image $I(x, y)$. Due to the separable, integer valued and small size nature of this edge detection approximation, it is relatively inexpensive in computations. Also, it produces significant behavior in the high frequency and sharp discontinuity intensity variation in the image. Although the formulation of Roberts edge detector approximation generally used form two dimensional images, this edge detector approximation can be further extended to other higher dimensions in case we have the higher dimensional image for the purpose of multi-dimensional edge detection.

Prewitt Edge Detector

Prewitt edge detector approximation was proposed by J. M. S. Prewitt presented the idea of an 3x3 Image Gradient Operator in 1970 [38]. It is a discrete two-dimensional differential operator used to emphasize and detect the gradient of the intensity function of image. The result of this operator corresponds either to the intensity gradient or the norm of the intensity gradient in the image. This is based on convolution of the image with two separable and integer valued horizontal and vertical operators, frequently known as masks. Given the input image $I(x, y)$ of size m by n, where x=1,2...,n and y=1,2,...,n are horizontal and vertical indices of the image

$$PF_x = \begin{bmatrix} +1 & 0 & -1 \\ +1 & 0 & -1 \\ +1 & 0 & -1 \end{bmatrix} \tag{2.6}$$

and

$$PF_y = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \tag{2.7}$$

Where PF_x and PF_y are derivative approximation in horizontal and vertical direction respectively. They are separable and integer valued small filters in horizontal and vertical directions. By convolving the $I(x, y)$ with G_x and G_y we obtain two different images with horizontal and vertical edge approximation

$$G_x = I(x, y) * PF_x \tag{2.8}$$

and

$$G_y = I(x, y) * PF_y \tag{2.9}$$

Where $*$is the convolution operator and G_x and G_y are the horizontal and vertical edge approximations respectively. The final edge image is obtained by computing the gradient approximation with equation:

$$E_P(x,y) = \sqrt{{G_x}^2 + {G_y}^2} \tag{2.10}$$

The resulting image $E_P(x,y)$ is known as Roberts Edge approximation of original image $I(x,y)$. Due to the separable, integer valued and small size nature of this edge detection approximation, it is relatively inexpensive in computations. Also, it produces significant behavior in the high frequency and sharp discontinuity intensity variation in the image. Although the formulation of Roberts edge detector approximation generally used form two dimensional images, this edge detector approximation can be further extended to other higher dimensions in case we have the higher dimensional image for the purpose of multi-dimensional edge detection.

Sobel-Feldman Edge Detector

One of the widely used edge detection techniques is the Sobel-Feldman Edge Detector. The Sobel-Feldman Edge Detector is based on the Sobel operator, which uses convolution with two 3x3 kernels to compute gradient approximations of the image in both horizontal and vertical directions. The gradient magnitude and direction can then be calculated, enabling edge detection [43, 42].

The kernels are as follows:

Horizontal Sobel Kernel:

$$SF_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Vertical Sobel Kernel:

$$SF_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Where SF_x and SF_y are derivative approximation in horizontal and vertical direction respectively. They are separable and integer valued small filters in horizontal and vertical directions. By convolving the $I(x, y)$ with G_x and G_y we obtain two different images with horizontal and vertical edge approximation

$$G_x = I(x, y) * SF_x \tag{2.11}$$

and

$$G_y = I(x, y) * SF_y \tag{2.12}$$

Where $*$is the convolution operator and G_x and G_y are the horizontal and vertical edge approximations respectively. The final edge image is obtained by computing the gradient approximation with equation:

$$E_S(x, y) = \sqrt{{G_x}^2 + {G_y}^2} \tag{2.13}$$

The resulting image $E_S(x, y)$ is known as Sobel-Fieldman Edge approximation of original image $I(x, y)$.

2.2.2 State of the art Edge Detectors

Holistically-Nested Edge Detector

The Holistically-Nested Edge Detector (HED) is a deep learning-based edge detection algorithm that was proposed by Xie et al. in 2015. HED is a two-stage detector that first predicts a coarse edge map and then refines it to produce a fine edge map [60].

The coarse edge map is predicted using a fully convolutional network (FCN). The FCN is trained to predict a pixel-wise probability of edge existence. The fine edge map is predicted using a cascade of FCNs. Each FCN in the cascade refines the edge map produced by the previous FCN. HED has several advantages over traditional edge detection algorithms. First, HED is able to produce more accurate edge maps, even in noisy images. Second, HED is able to detect edges of different scales and orientations. Third, HED is relatively fast and efficient to train and deploy.

HED has been used successfully in a variety of applications, including image segmentation, object detection, and medical image analysis.

Stage 1: Coarse edge map prediction

The coarse edge map is predicted using a FCN with a large receptive field. The FCN is trained to predict a pixel-wise probability of edge existence. The output of the FCN is a binary image, where pixels with a high probability of edge existence are white and pixels with a low probability of edge existence are black.

Stage 2: Fine edge map refinement

The fine edge map is predicted using a cascade of FCNs. Each FCN in the cascade refines the edge map produced by the previous FCN. The FCNs in the cascade have smaller receptive fields than the FCN used to predict the coarse edge map. This allows the FCNs in the cascade to focus on detecting finer details in the edge map.

The output of the final FCN in the cascade is the fine edge map. The fine edge map is a binary image, where pixels with a high probability of edge existence are white and pixels with a low probability of edge existence are black. HED has been shown to be more accurate than traditional edge detection algorithms, such as the Sobel operator and the Canny edge detector. HED is also more robust to noise and can detect edges of different scales and orientations. HED is a powerful edge detection algorithm that can be used in a variety of applications. It is relatively fast and efficient to train and deploy, and it produces accurate edge maps, even in noisy images[60].

Richer Convolutional Features Edge Detector

The Richer Convolutional Features (RCF) Edge Detector is a deep learning-based edge detection algorithm that was proposed by Liu et al. in 2022 [30]. RCF edge detector is an improvement over the HED algorithm, and it is able to produce more accurate edge maps, especially in noisy images.

RCF edge detector uses a richer set of convolutional features than HED. This allows RCF edge detector to better capture the complex features of edges. RCF edge detector also uses a more sophisticated loss function than HED. This loss function encourages RCF edge detector to produce edge maps that are both accurate and smooth.RCF edge detector uses a richer set of convolutional features than HED. This richer set of features includes features that capture the complex features of edges, such as curvature and texture.

RCF edge detector uses a more sophisticated loss function than HED. This loss function encourages RCF-ED to produce edge maps that are both accurate and smooth. RCF edge detector is trained on a dataset of edge-labeled images. The training data is used to train the RCF edge detector network to predict edge maps.Once the RCF edge detector network is trained, it can be used to predict edge maps from new images. The RCF edge detector network outputs a probability map, where each pixel in the map represents the probability of an edge existing at that pixel [30].

Bi-Directional Cascade Network Perceptual Edge Detector

The Bi-directional Cascade Network (BCN) for Perceptual Edge Detection is a deep learning-based edge detection algorithm that was proposed by He et al. in 2019 [16]. BCN is a two-stage network that first predicts a coarse edge map and then refines it to produce a fine edge map. BCN is inspired by the observation that human perception of edges is influenced by both low-level features, such as intensity gradients, and high-level features, such as contextual information. To capture both low-level and high-level features, BCN uses a bi-directional cascade architecture.

In the first stage of BCN, a coarse edge map is predicted using a bottom-up approach. The bottom-up approach starts from low-level features and gradually combines them to extract higher-level features. In the second stage of BCN, the coarse edge map from the first stage is refined using a top-down approach. The top-down approach starts from high-level features and gradually combines them to refine the coarse edge map.

BCN has been shown to outperform state-of-the-art edge detection algorithms on a variety of edge detection benchmarks. BCN is also more robust to noise and can detect edges of different scales and orientations. Here is an overview of the BCN algorithm:

Bi-directional cascade architecture - BCN uses a bi-directional cascade architecture to capture both low-level and high-level features. The bi-directional cascade architecture consists of two stages: a bottom-up stage and a top-down stage.

Bottom-up stage : The bottom-up stage starts from low-level features and gradually combines them to extract higher-level features. The bottom-up stage uses a series of convolutional layers to extract features from the input image. The features from the convolutional layers are then passed through a series of pooling layers to reduce the spatial dimensions of the features. Top-down stage: The top-down stage starts from high-level features and gradually combines them to refine the edge map. The top-down stage uses a series of convolutional layers to extract features from the input image. The features from the convolutional layers are then passed through a series of upsampling layers to increase the spatial dimensions of the features.

Coarse edge map prediction : The coarse edge map is predicted using the bottom-up stage of BCN. The coarse edge map is a binary image, where pixels with a high probability of edge existence are white and pixels with a low probability of edge existence are black.

Fine edge map refinement : The fine edge map is refined using the top-down stage of BCN. The top-down stage uses the coarse edge map as input and produces a refined edge map as output. The refined edge map is more accurate than the coarse edge map and can detect edges of different scales and orientations.

Training and inference : BCN is trained on a dataset of edge-labeled images. The training data is used to train the BCN network to predict edge maps.

Once the BCN network is trained, it can be used to predict edge maps from new images. The BCN network outputs a probability map, where each pixel in the map represents the probability of an edge existing at that pixel.BCN is a powerful edge detection algorithm that can be used in a variety of applications. It is especially well-suited for applications where accurate edge detection is important, such as image segmentation and object detection [16].

Dense Extreme Inception Network Edge Detector

The Dense Extreme Inception Network (DexiNed) architecture is a combination of the DenseNet and InceptionNet architectures. DenseNets are deep neural networks that are connected in a dense manner, meaning that each layer is connected to all of the previous layers. This allows DenseNets to learn long-range dependencies in the data. InceptionNets are deep neural networks that use a combination of different convolution operations to extract features from the data. This allows InceptionNets to extract features at different levels of abstraction [36].

The DexiNed architecture combines the dense connectivity of DenseNets with the feature extraction capabilities of InceptionNets. This allows DexiNed to extract both low-level and high-level features from the input image. This is important for edge detection, as edges can vary in scale and orientation.

Coarse edge map prediction stage : The coarse edge map prediction stage of DexiNed uses a series of DenseNet and InceptionNet layers to extract features from the input image. The features extracted by the DenseNet and InceptionNet layers are then passed through a series of pooling layers to reduce the spatial dimensions of the features. This reduces the computational cost of the network and also helps to prevent overfitting. The pooled features are then used to predict a coarse edge map. The coarse edge map is a binary image, where pixels with a high probability of edge existence are white and pixels with a low probability of edge existence are black. The coarse edge map prediction stage uses a technique called extreme learning machines (ELMs). ELMs are a type of machine learning algorithm that can be trained very quickly. This is important for edge detection, as edge detection algorithms are often used in real-time applications.

Fine edge map refinement stage : The fine edge map refinement stage of DexiNed uses a series of DenseNet and InceptionNet layers to refine the coarse edge map. The features extracted by the DenseNet and InceptionNet layers in the fine edge map refinement stage are then passed through a series of upsampling layers to increase the spatial dimensions of the features. This allows the network to refine the coarse edge map at a finer level of detail. The fine edge map refinement stage also uses a technique called skip connections. Skip connections allow the network to learn long-range dependencies in the image data. This helps the network to produce more accurate edge maps, especially in areas where the edges are weak or ambiguous.

Training and inference : DexiNed is trained on a dataset of edge-labeled images. The training data is used to train the DexiNed network to predict edge maps. Once the DexiNed network is trained, it can be used to predict edge maps from new images. The DexiNed network outputs a probability map, where each pixel in the map represents the probability of an edge existing at that pixel [36].

2.3 Definition of the Problem

2.3.1 Challenges in Edge detection in MRI image of Brain

Edge detection methods for brain tissue segmentation applications are having following problems:

- MRI images of the brain often have low contrast, which can make it difficult to distinguish between different tissues and their structures.
- MRI images can be affected by various sources of noise, such as motion artifacts, thermal noise, and radio-frequency interference. Noise can result in spurious edges or false positives, which can degrade the accuracy of edge detection algorithms.
- In MRI images, voxels may contain a mixture of different tissues, which can result in partial volume effects. This can make it challenging to accurately locate edges at tissue boundaries.
- The structure of the brain can vary widely across individuals, which can make it challenging to develop edge detection algorithms that are generalizable across different subjects.
- MRI images can be affected by various types of image artifacts, such as shading artifacts, ghosting, and ringing. These artifacts can result in false edges or edge gaps, which can affect the accuracy of edge detection algorithms.
- The spatial resolution of MRI images can affect the accuracy of edge detection algorithms, particularly for small or subtle edges.
- Edges can occur at different scales and orientations in an image. Detecting edges at all scales and orientations requires sophisticated algorithms and a careful selection of parameters.
- Edges can be characterized by changes in intensity, but intensity variations can occur for reasons other than edges, such as shadows, reflections, or texture. This makes it difficult to distinguish between true edges and false edges.
- Edge detection algorithms can be computationally intensive, particularly for large or high-resolution images. This can limit their usefulness in real-time applications or on devices with limited processing power.

- Edge detection can be subjective and depend on the specific algorithm and parameters used. Different algorithms can produce different results, and the choice of the best algorithm often depends on the specific application

2.3.2 Problem Definition

MRI images are susceptible to noise from various sources, which can introduce spurious edges in the resulting images. These spurious edges lead to false positives, consequently diminishing the accuracy of edge detection algorithms. As the level of noise in MRI images escalates, the performance of edge detectors tends to deteriorate. Therefore, there is a growing need for edge detectors that can effectively handle the increasing noise levels present in MRI images.

2.4 Objective and Scope of work

2.4.1 Objective of work

- To analyze the effect on the performance of edge detectors as a result of the increasing amount of noise in MRI image of the human brain.
- To develop an edge detector for the detection of edges in the MRI image of the human brain.
- To develop an edge detector with the ability to withstand the increasing amount of noise in the MRI image of the human brain.
- To determine the performance of the developed edged detector with respect to the increasing amount of noise in the MRI image of the human brain.

2.4.2 Scope of work

- We have focused on the MRI image of the human brain.
- We have focused on determining the effect on the performance of edge detectors as a result of the increasing amount of noise in the MRI image.
- We have focused on proposing an edge detector with the ability to withstand the increasing amount of noise in the MRI image.

Chapter 3

Methodology

This Chapter focuses on the methodology employed in this study. We commence with a comprehensive discussion of Monotonic and Bitonic signals, accompanied by graphical representations for better understanding. Subsequently, we delve into the intricacies of Bitonic filters. The chapter then progresses to the heart of our research, where we introduce the Proposed Bitonic edge detector, offering a detailed mathematical representation. Furthermore, we explore a structural variation of the Bitonic edge detector within the same chapter.

3.1 Monotonic and Bitonic Signals

Here, the Monotonic and Bitonic signals are described with graphical representations.

3.1.1 Monotonic Signal

A monotonic signal is a type of signal or waveform that consistently exhibits a non-decreasing or non-increasing behavior over its entire duration. In other words, a monotonic signal either continuously increases in amplitude (positive monotonic) or continuously decreases in amplitude (negative monotonic), without any significant reversals or oscillations [18].

The monotonic signals are Non-Decreasing Monotonic Signal and Non-Increasing Monotonic Signal.

Non-Decreasing Monotonic Signal

In 3.1 a non-decreasing monotonic signal, the amplitude (or value) of the signal remains the same or increases as you move from the beginning to the end of the signal. There may be minor fluctuations, but the general trend is upward or constant.

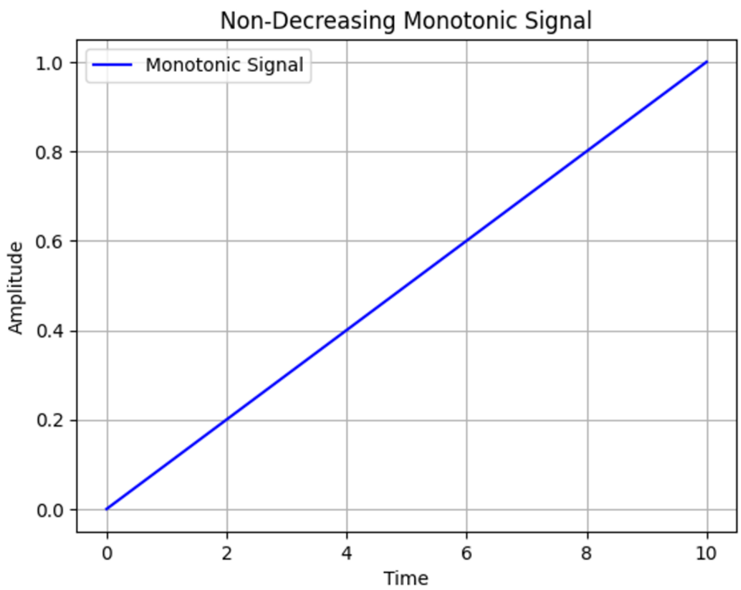

Fig. 3.1 The Non-Decreasing Monotonic Signal

Non-Increasing Monotonic Signal

In 3.2 a non-increasing monotonic signal, the amplitude (or value) of the signal remains the same or decreases as you move from the beginning to the end of the signal. Similar to non-decreasing monotonic signals, there may be minor fluctuations, but the overall trend is downward or constant.

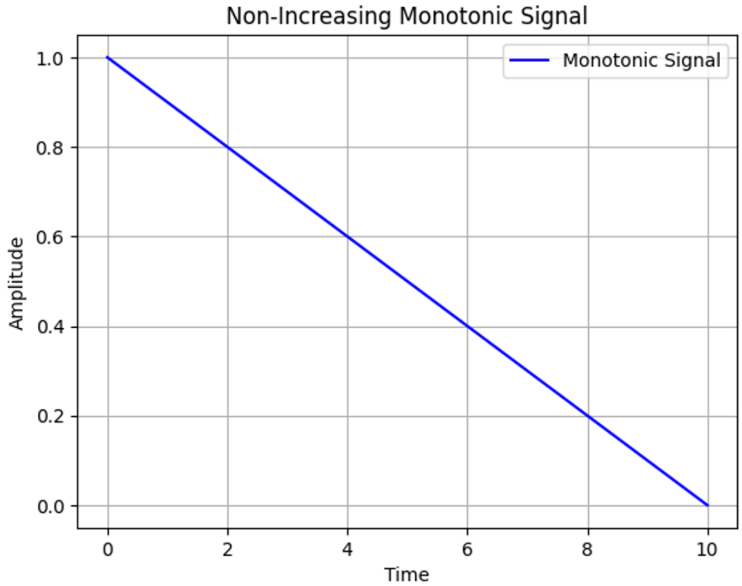

Fig. 3.2 The Non-Increasing Monotonic Signal

Monotonic signals are commonly encountered in various fields, including mathematics, physics, engineering, and signal processing. They are often used in the analysis and modeling of real-world phenomena where a consistent trend, such as growth or decay, is observed. Monotonic signals play a crucial role in areas like data analysis, control systems, and time-series analysis, where understanding the direction and magnitude of change is essential [35, 18].

3.1.2 Bitonic Signal

A bitonic signal is a type of signal or waveform that exhibits a specific pattern of change in amplitude or value. In a bitonic signal, the amplitude first continuously increases (rises) and then continuously decreases (falls) or vice versa over its entire duration. In other words, a bitonic signal has a single peak or valley within its waveform, and this peak or valley is the highest or lowest point in the signal [4].

The bitonic signal shows peak or valley and symmetry properties.

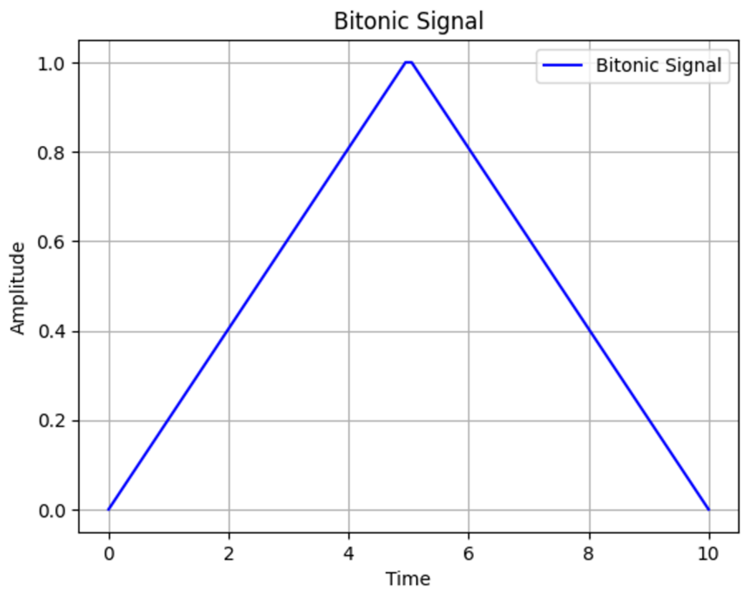

Fig. 3.3 A bitonic signal featuring only one peak

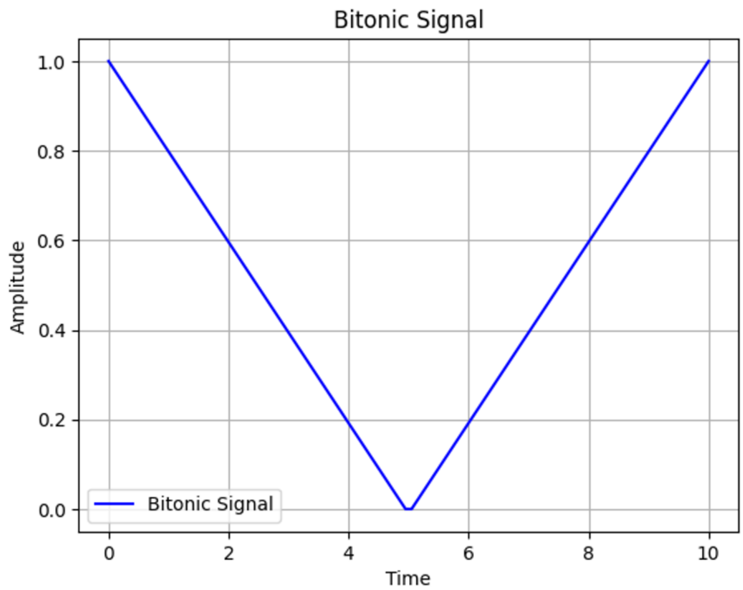

Fig. 3.4 A bitonic signal featuring only one valley

A bitonic signal has one and only one peak or valley. The amplitude gradually rises to reach this peak or falls to reach this valley, and after that, it follows a decreasing or increasing trend, respectively.In 3.3 the bitonic signal shows only one peak. In 3.4 the bitonic signal shows only one valley. Apart from the single peak or valley, there are no other local maxima or minima within the signal. The amplitude change is monotonic on either side of the peak or valley. Bitonic signals often exhibit a degree of symmetry. If the signal starts with a rising pattern, it will end with a falling pattern, and vice versa. In 3.3 and 3.4 the signals shows symmetry around the peak and the valley point respectively. Bitonic signals are encountered in diverse fields such as mathematics, computer science, and signal processing. They can represent phenomena like response times, sorting algorithms, and certain types of waveforms.

The concept of bitonic signals and bitonicity has applications in various fields, including signal processing, algorithm design, and the analysis of data with specific amplitude patterns. [7].

3.2 Bitonic Filter

Bitonic filters are a type of nonlinear filter that is used in signal processing for noise reduction. They are based on the definition of a bitonic signal, which is a signal that has only one local maximum or minimum within a specific range. Bitonic filters work by ranking the data points in the signal and then replacing each data point with a combination of the surrounding ranked data points. This process preserves any bitonic signals in the signal while rejecting anything else [5, 46].

Bitonic filters are better at preserving edges in signals than other types of filters, such as median filters and Gaussian filters. This is because bitonic filters are specifically designed to preserve bitonic signals, which are signals that have only one local maximum or minimum within a specific range. Bitonic filters are also effective at reducing noise in signals. This is because bitonic filters reject any data points that are not part of a bitonic signal. Bitonic filters are applicable to a wide range of signal and noise types. This makes them a versatile tool for signal processing applications. Bitonic filters can be used for a variety of signal processing tasks like signal denoising, audio denoising, medical signal processing, industrial signal processing and image denoising.Bitonic filters can be used to reduce noise in images. Bitonic filters can be used to reduce noise in audio signals while preserving the original sound quality. Bitonic filters can be used to improve the quality of medical signals, such as EEG and ECG signals. Bitonic filters can be used to improve the quality of industrial signals, such as sensor data and control signals [58, 26].

In image denoising, bitonic filters are often used to reduce noise in noisy images while preserving edges and detail. This can be useful for improving the visual quality of images, such as for medical imaging or industrial inspection. In audio denoising, bitonic filters can be used to reduce noise in noisy audio signals while preserving the original sound quality. This can be useful for improving the audio quality of music, movies, and other audio recordings.In medical signal processing, bitonic filters can be used to improve the quality of medical signals, such as EEG and ECG signals. This can be useful for detecting abnormalities in medical signals and for improving the diagnostic accuracy of medical tests [48]. In industrial signal processing, bitonic filters can be used to improve the quality of industrial signals, such as sensor data and control signals. This can be useful for improving the reliability and performance of industrial systems [55, 46].

3.3 Bitonic Edge Detector

Rank filters are a class of nonlinear filters that preserve monotonic signals, which are signals that have a single local maximum or minimum within a given range. This property makes rank filters well-suited for reducing impulsive noise, which is noise that has a sharp change in value.

Rank filters work by ranking the data points in a local window and then selecting a specific centile of the ranked data as the output. For example, the median filter selects the

50^{th} centile, which is the middle value in the ranked data. Other centiles can be selected to achieve different noise reduction characteristics. Applying a rank filter with a centile of 100 (a maximum, also known as a dilation) followed immediately by a rank filter with a centile of 0 (a minimum, also known as an erosion) is called a morphological closing operation. This operation preserves signals with a local maximum and rejects signals with a local minimum. Reversing the order of the filters produces a morphological opening operation, which has the opposite effect.

Morphological closing and opening operations are widely used in signal processing, particularly for granulometry, which is the study of the size distribution of particles in a sample.

The authors of [48, 46] propose a new type of robust opening operation that uses a small centile c instead of the minimum for the erosion step and (100 - c) instead of the maximum for the dilation step. This operation is similar to the rank-max opening and soft-opening operations, but it has some advantages. For example, it allows for more control over impulsive noise rejection, since any impulse that takes up less than c of the filter range will be rejected.

Let x be a signal or image, and $r_{w,c}$ be the rank filter given by

$$r_{w,c} = c^{th} \underset{i \in w}{\text{centile}} \{x_i\} \tag{3.1}$$

where $r_{w,c}$ is the rank filter, w is the filter window or the structuring element for the image, $\mid w \mid$ is the window length or the number of elements in the structuring element for the image and c is the chosen centile.

The robust opening $O_{w,c}(x)$ and robust closing $C_{w,c}$ can be defined as

$$O_{w,c}(x) = r_{w,100} - c\left(r_{w,c}(x)\right) \tag{3.2}$$

$$C_{w,c}(x) = r_{w,c}\left(r_{w,100} - c(x)\right) \tag{3.3}$$

where $O_{w,c}(x)$ is the robust opening and $C_{w,c}(x)$ is the robust closing operation performed on the signal or the image x.

let $\epsilon_O(x)$ and $\epsilon_C(x)$ be the smoothed opening and closing errors respectively defined as

$$\epsilon_O(x) = \mid G_\sigma(x - O_{w,c}(x)) \mid \tag{3.4}$$

and

$$\epsilon_C(x) = \mid G_\sigma(C_{w,c}(x) - x) \mid \tag{3.5}$$

where $\epsilon_O(x)$ and $\epsilon_C(x)$ be the smoothed opening and closing errors computed over the signal or image x respectively. And $G_\sigma(x)$ is the Gaussian linear filter used to weight the opening and closing operations.Here $G_\sigma(x)$ is used to smooth the opening and closing errors later used as weight the opening and closing errors.

Let $\underset{Bitonic}{E_{w,c}}$ be the Bitonic edge computed with w, the filter window or the structuring element for the image, and c, the chosen centile. The $\underset{Bitonic}{E_{w,c}}$ can be computed as follows:

$$\underset{Bitonic}{E_{w,c}} = \frac{\epsilon_O(x)\dfrac{dC_{w,c}(x)}{dx} + \epsilon_C(x)\dfrac{dO_{w,c}(x)}{dx}}{\epsilon_O(x) + \epsilon_C(x)} \tag{3.6}$$

where $\underset{Bitonic}{E_{w,c}}$ is the Bitonic edge computed with w, the filter window or the structuring element for the image, and c, the chosen centile.

3.4 Structural Variation Bitonic Edge Detector

Adaptive morphology is a field of research that explores how to use morphological operations in a more intelligent and flexible way. Traditional morphological operations use a fixed structuring element, which can be limiting in some applications. Adaptive morphology seeks to develop methods that can automatically adjust the structuring element based on the input data. Adaptive morphology in image processing refers to the use of morphological operations with adaptive or variable-sized structuring elements. Traditional morphological operations use fixed-size structuring elements, which may not be suitable for all image processing tasks, especially when dealing with images containing objects of varying sizes, shapes, or orientations [14, 27].

Adaptive morphology addresses these limitations by dynamically adjusting the size, shape, or orientation of the structuring element based on local image characteristics. The goal is to adapt the morphological operations to the specific features of the objects or regions within the image [53, 54, 52].

Authors of [47] presented a novel morphology-based noise reduction filter called the structurally varying bitonic filter (SVBitonic filter). The SVBitonic filter is a robust filter that can effectively remove impulsive noise while preserving edges in images. The SVBitonic filter works by adaptively adjusting the size and shape of its structuring element based on the local structure of the image.

By introducing a controlling parameter m for the transition of $O_{w,c}(x)$ and $C_{w,c}(x)$, we can write equation 3.4 as

$$\epsilon_O^m(x) = \mid G_\sigma(x - O_{w,c}(x)) \mid^m \tag{3.7}$$

and equation 3.5 as

$$\epsilon_C^m(x) = |\ G_\sigma(C_{w,c}(x) - x)\ |^m \tag{3.8}$$

where m is the transition controlling parameter and controls the transition of $O_{w,c}(x)$ and $C_{w,c}(x)$. Setting m to 1 gives a gradual transition, and results in the same expression as in equation 3.4 and equation 3.5. Where as setting m to 3 gives a more sudden transition, which improves the performance [47]. The details on derivation of the controlling parameter m is discussed in details in the research work of [47]. The details on set of structuring elements of the controlling parameter m is also discussed in details in the research work of [47].

By considering equations 3.7 and 3.8, the Biotonic edge detector equation 3.7 becomes the Structural Variation Bitonic Edge Detector as

$$\underset{SVBitonic}{E_{w,c}} = \frac{\epsilon_O^m(x)\dfrac{d\left(C_{w,c}(x) - \epsilon_C\right)}{dx} + \epsilon_C^m(x)\dfrac{d\left(O_{w,c}(x) + \epsilon_O\right)}{dx}}{\epsilon_O^m(x) + \epsilon_C^m(x)} \tag{3.9}$$

where $\underset{SVBitonic}{E_{w,c}}$ represents the Structural Variation Bitonic Edge Detector computed using w as the filter window or the structuring element for the image, c as the chosen centile, and m as the transition controlling parameter.

Chapter 4

Experimental Setup and Results

In Chapter 4, we turn our attention to the experimental aspects of our study. This chapter provides a detailed account of the experimental setup, focusing on the MR image dataset and the associated noise characteristics. We meticulously document the outcomes of applying both traditional edge detectors and state-of-the-art edge detectors to this dataset. The resulting images are showcased and analyzed. Additionally, we present the results of our Proposed Bitonic edge detector, complete with a discussion of its mathematical underpinnings. Furthermore, we delve into the structural variation of the Bitonic filter and its associated results, facilitating a comparative analysis with the outcomes of traditional and state-of-the-art edge detectors.

4.1 Dataset

As the use of computer-aided methods to analyze medical images grows, so does the need to validate these methods. However, there is no "ground truth" or gold standard for analyzing in vivo data. [21, 9, 10, 22] address this challenge by providing a Simulated Brain Database (SBD). The SBD contains a set of realistic MRI data volumes generated by an

MRI simulator. Neuroimaging researchers can use these data to evaluate the performance of image analysis methods under known conditions [2, 1].

Simulated Brain Web: A Comprehensive Virtual Brain Database and Simulator for Neuroimaging Research [49], describes the development of a comprehensive virtual brain database and simulator called BrainWeb. BrainWeb is designed to provide researchers with a realistic and customizable platform for simulating brain MRI data. The database includes a variety of anatomical models, MRI sequences, and noise levels, allowing researchers to create simulated data that closely resembles real-world MRI scans.

The Simulated Brain Database (SDB) of BrainWeb: A Tool for Validating and Benchmarking Brain Image Analysis Algorithms [56], describes how BrainWeb can be used to validate and benchmark brain image analysis algorithms. The authors demonstrate how BrainWeb can be used to create simulated data with known ground truth, which can then be used to evaluate the performance of different image analysis algorithms under controlled conditions.

The SBD includes simulated brain MRI data based on two anatomical models: healthy normal and multiple sclerosis (MS). For each model, full 3D data volumes were simulated using three MRI sequences (T1-, T2-, and proton-density-weighted) and a variety of slice thicknesses, noise levels, and intensity non-uniformity [49, 56].

SDB describe a valuable tool for researchers who are developing and evaluating brain image analysis algorithms. BrainWeb provides a realistic and customizable platform for simulating brain MRI data, which can be used to create simulated data that closely resembles real-world MRI scans. This allows researchers to validate and benchmark their algorithms under controlled conditions, which can lead to more accurate and reliable results. [57] used the SDB to evaluate the performance of segmentation algorithms for Alzheimer's disease. [28] used the SDB to evaluate the performance of lesion detection algorithms for stroke. [29] used the SDB to evaluate the performance of connectivity analysis algorithms for multiple sclerosis. [57, 28, 29] demonstrate that the SDB of BrainWeb can be used to evaluate the performance of brain image analysis algorithms for a variety of neurological disorders. This can help researchers to develop more accurate and reliable algorithms for diagnosing and monitoring these disorders.

The BrainWeb MRI image dataset is a widely used resource in the field of medical image processing and neuroimaging research. It provides a set of simulated MRI images of the human brain, including T1-weighted, T2-weighted, and proton density (PD)-weighted images. These simulated images are created with carefully controlled noise levels and other parameters to mimic real-world MRI scans. The BrainWeb dataset incorporates Rician noise, which is a type of noise commonly observed in MRI images. Rician noise arises due to the complex nature of MRI data, where the signal and noise components are both complex-valued. It is characterized by a non-central chi-squared probability distribution and can have a significant impact on image quality and analysis. One of the strengths of the BrainWeb dataset is that it provides images with varying levels of noise. Researchers can choose from different levels of noise to simulate MRI images with different signal-to-noise ratios (SNR). This allows them to test the robustness and performance of image processing algorithms under various noise conditions. Users can adjust parameters such as the noise level, contrast, and spatial resolution when generating images from the BrainWeb dataset. This customization capability makes it a valuable tool for evaluating and comparing different image processing techniques. The noise in the BrainWeb MRI dataset is generated in a way that closely resembles the noise characteristics found in actual MRI scans. This makes it suitable for assessing the performance of algorithms in real-world scenarios. Researchers often use the BrainWeb MRI dataset to test and validate various image processing algorithms, including noise reduction techniques, image segmentation methods, and image registration algorithms. By utilizing this dataset, they can evaluate how well their algorithms perform in the presence of realistic noise levels, helping to improve the quality and accuracy of medical image analysis and diagnosis. In the table 4.1, the MR images for the increasing noise levels from 0% to 9% are presented.

Table 4.1 The Original MR images with increasing Noise percentages.

Noise(%)	Original MR Image
0	
1	
3	

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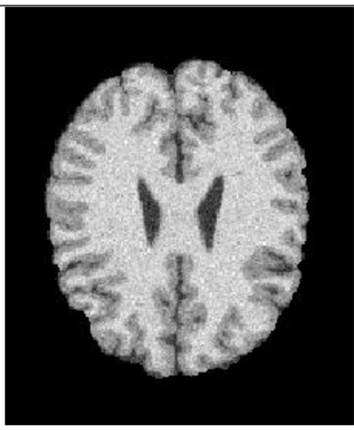
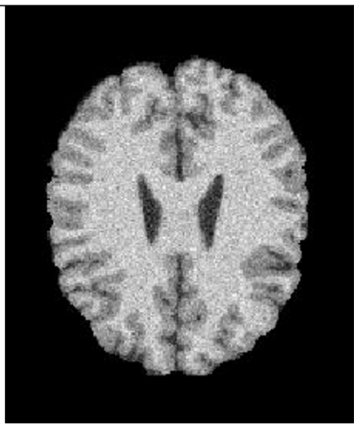
Table 4.1 The Original MR images with increasing Noise percentages(cont.).

Noise(%)	Original MR Image
5	
7	
9	

4.2 Results of Traditional Edge Detectors

In this section, the results of different traditional edge detector on MR image dataset is discussed. After applying the traditional edge detector to the MR image dataset, resulting images under various noise levels are obtained.

4.2.1 Results of Roberts Edge Detector

Table 4.2 represents the results of Roberts edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Roberts edge detector degrade as the amount of noise in the MR image dataset is increasing. The Roberts edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. It is showing degraded results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs poor in the higher amount of the noise presents in the MR image dataset. These leads to higher amount of spurious edges detected in the MR image dataset because of higher amount of noise present in the MR image datasets.

Table 4.2 Results of the Roberts Edge Detector for different noise levels in MR image .

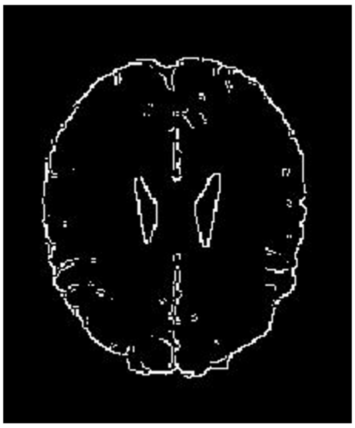
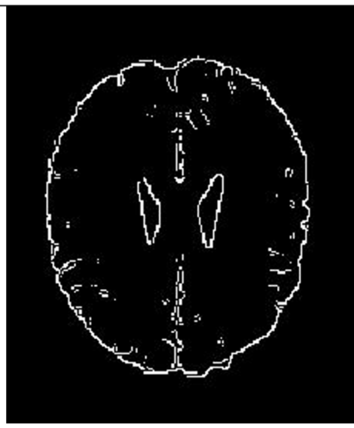
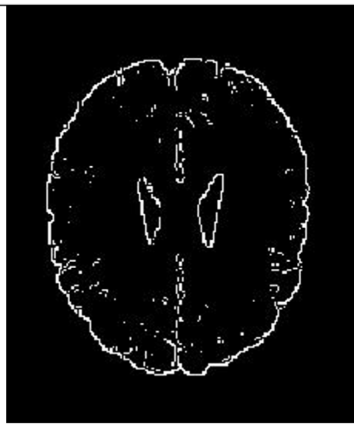
Noise(%)	Original MR Image	Roberts Edge Detector
0		
1		
3		

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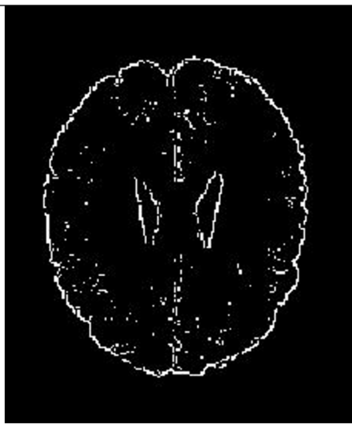
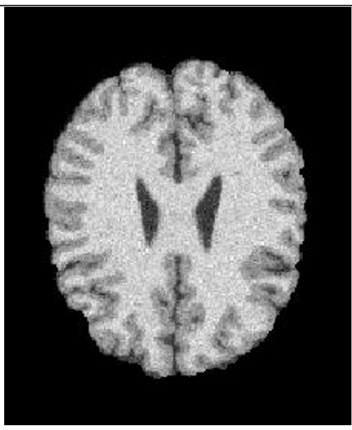
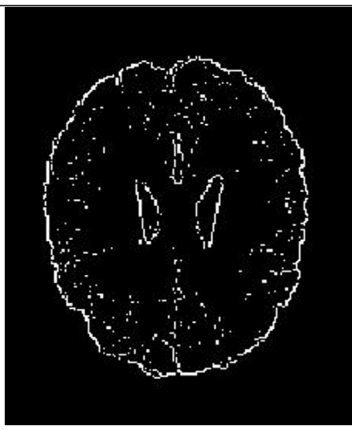
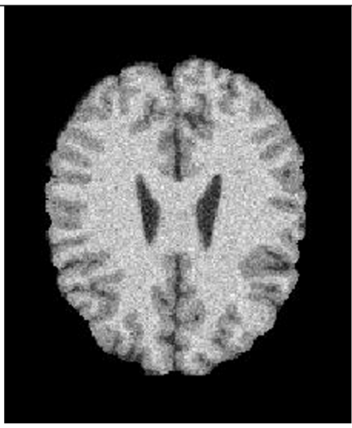
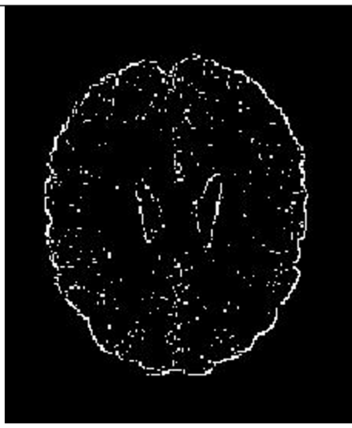
Table 4.2 Results of the Roberts Edge Detector(cont.).

Noise(%)	Original MR Image	Roberts Edge Detector
5		
7		
9		

4.2.2 Results of Prewitt Edge Detector

Table 4.3 represents the results of Prewitt edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Prewitt edge detector degrade as the amount of noise in the MR image dataset is increasing. The Prewitt edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. It is showing degraded results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs poor in the higher amount of the noise presents in the MR image dataset. These leads to higher amount of spurious edges detected in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Prewitt edge detector are comparatively improved than that of the Roberts edge detector of the MR image dataset in the presence of increased amount of the noise.

Table 4.3 Results of the Prewitt Edge Detector for different noise levels in MR image.

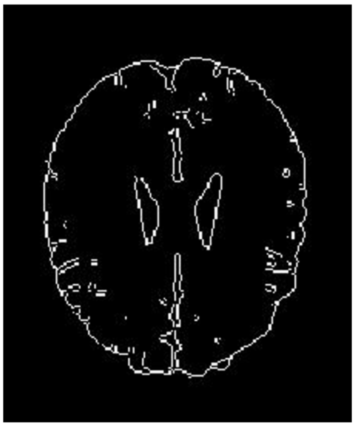
Noise(%)	Original MR Image	Prewitt Edge Detector
0		

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Table 4.3 Results of the Prewitt Edge Detector(cont.).

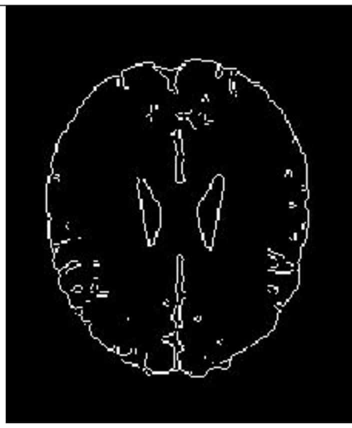
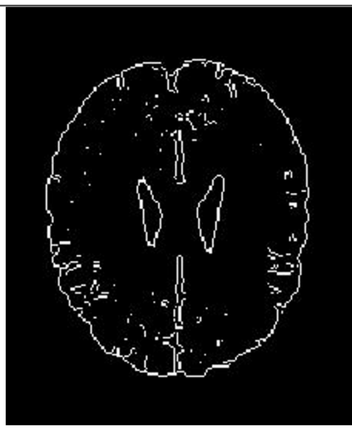
Noise(%)	Original MR Image	Prewitt Edge Detector
1		
3		
5		

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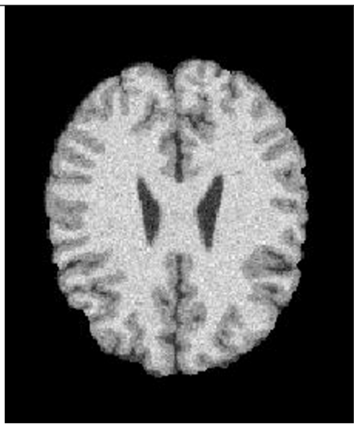
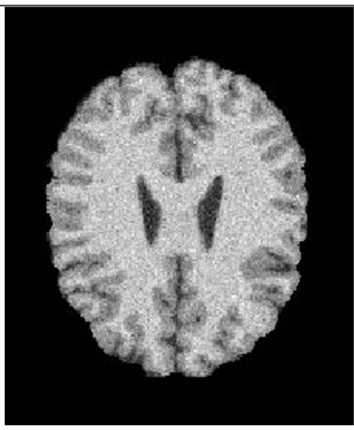
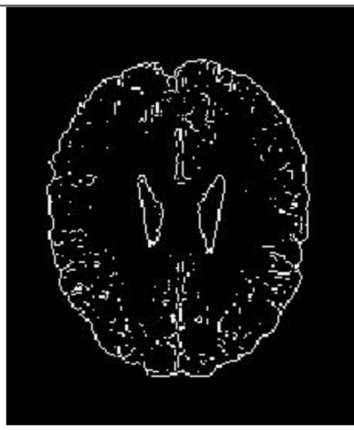
Table 4.3 Results of the Prewitt Edge Detector(cont.).

Noise(%)	Original MR Image	Prewitt Edge Detector
7		
9		

4.2.3 Results of Sobel-Feldman Edge Detector

Table 4.4 represents the results of Sobel-Feldman edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Sobel-Feldman edge detector degrade as the amount of noise in the MR image dataset is increasing. The Sobel-Feldman edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. It is showing degraded results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs poor in the higher amount of the noise presents in the MR image dataset. These leads to higher amount of spurious edges detected in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Sobel-Feldman edge detector are comparatively improved than that of the Prewitt and Roberts edge detector of the MR image dataset in the presence of increased amount of the noise.

Table 4.4 Results of the Sobel-Feldman Edge Detector for different noise levels in MR image.

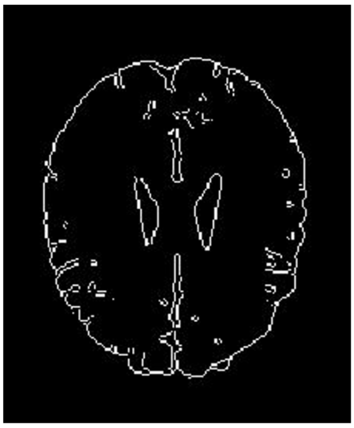
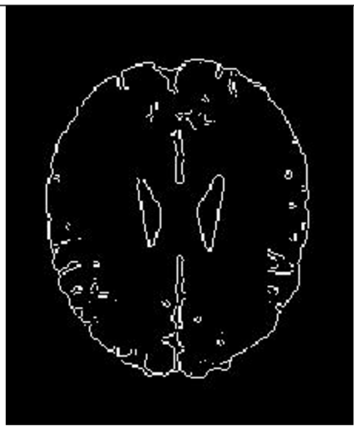
Noise(%)	Original MR Image	Sobel-Feldman Edge Detector
0		
1		

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Table 4.4 Results of the Sobel-Feldman Edge Detector(cont.).

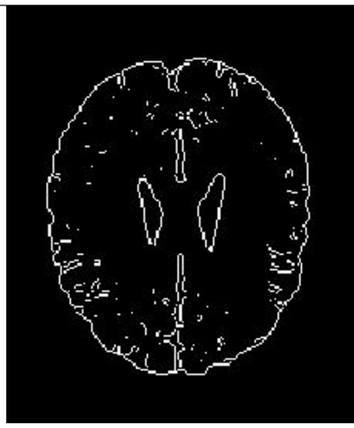
Noise(%)	Original MR Image	Sobel-Feldman Edge Detector
3		
5		
7		

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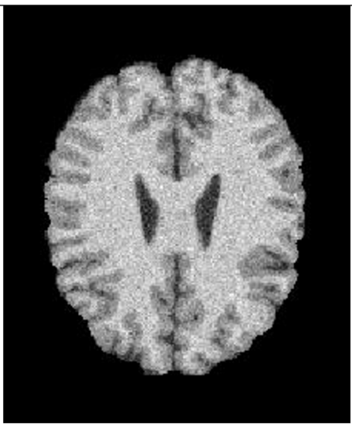
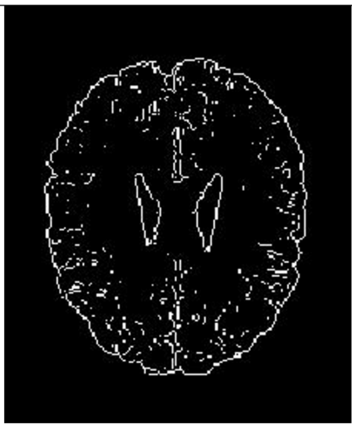
Table 4.4 Results of the Sobel-Feldman Edge Detector(cont.).

Noise(%)	Original MR Image	Sobel-Feldman Edge Detector
9		

4.3 Results of State-of-the-Art Edge Detectors

In this section, the results of different state-of-the-art edge detector on MR image dataset is discussed. After applying the state-of-the-art edge detector to the MR image dataset, resulting images under various noise levels are obtained.

4.3.1 Results of Holistically-Nested Edge Detector

Table 4.5 represents the results of Holistically-Nested edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Holistically-Nested edge detector degrade as the amount of noise in the MR image dataset is increasing. The Holistically-Nested edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. Same time it is not able to detect very finer edges in the MR image dataset. It is showing degraded results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs poor in the higher amount of the noise presents in the MR image dataset. These leads inability to detect the finer edges in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Holistically-Nested edge detector are comparatively improved than that of the traditional edge detectors of the MR image dataset in the presence of increased amount of the noise.

Table 4.5 Results of the Holistically-Nested Edge Detector for different noise levels in MR image.

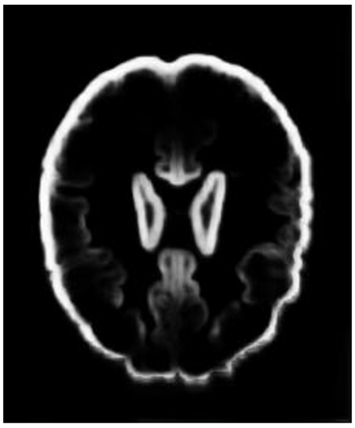
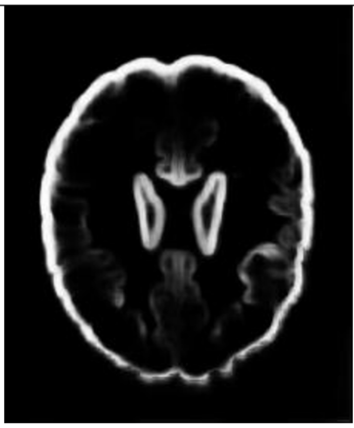
Noise(%)	Original MR Image	Holistically-Nested Edge Detector
0		
1		

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Table 4.5 Results of the Holistically-Nested Edge Detector(cont.).

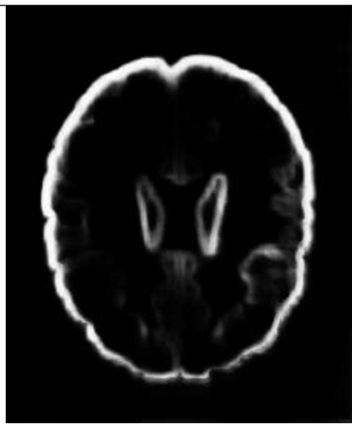
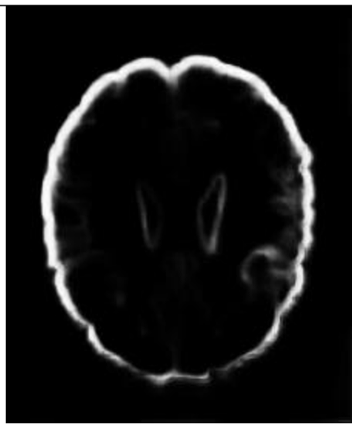
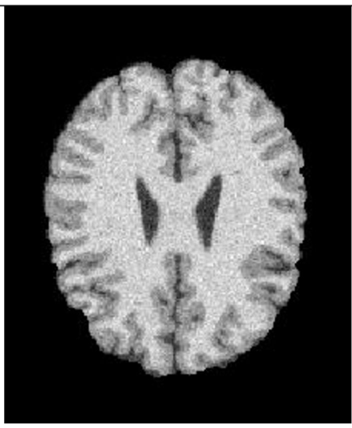
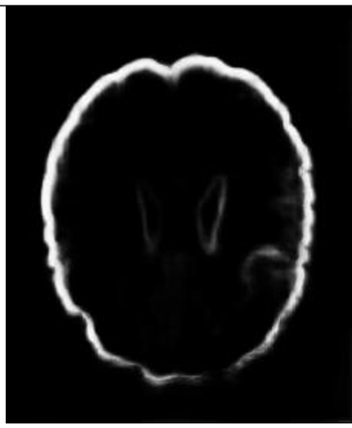
Noise(%)	Original MR Image	Holistically-Nested Edge Detector
3		
5		
7		

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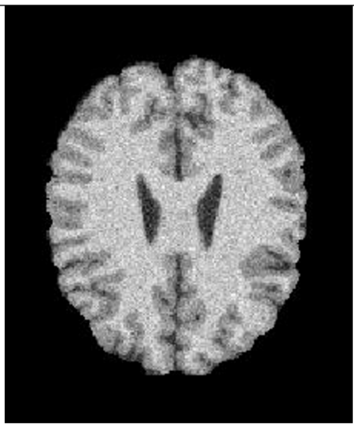
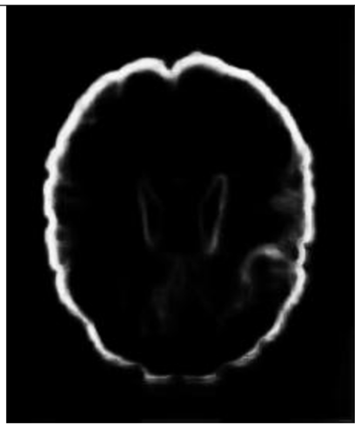
Table 4.5 Results of the Holistically-Nested Edge Detector(cont.).

Noise(%)	Original MR Image	Holistically-Nested Edge Detector
9		

4.3.2 Results of Richer Convolutional Features Edge Detector

Table 4.6 represents the results of Richer Convolutional Features edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Richer Convolutional Features edge detector degrade as the amount of noise in the MR image dataset is increasing. The Richer Convolutional Features edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. Same time it is not able to detect very finer edges in the MR image dataset. It is showing degraded results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs poor in the higher amount of the noise presents in the MR image dataset. These leads inability to detect the finer edges in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Richer Convolutional Features edge detector are comparatively improved than that of the traditional edge detectors as well as the Holistically-Nested edge detector of the MR image dataset in the presence of increased amount of the noise.

Table 4.6 Results of the Richer Convolutional Features Edge Detector for different noise levels in MR image.

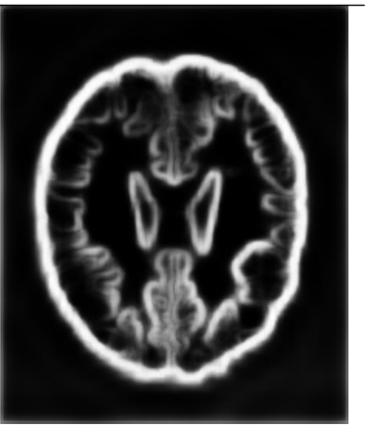
Noise(%)	Original MR Image	Richer Convolutional Features Edge Detector
0		
1		

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Table 4.6 Results of the Richer Convolutional Features Edge Detector(cont.).

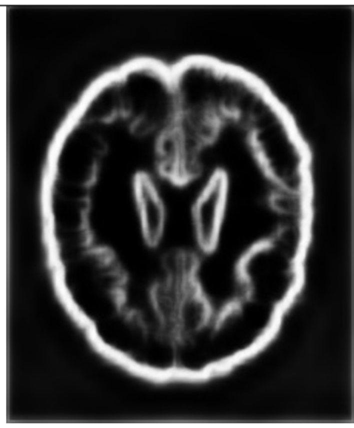
Noise(%)	Original MR Image	Richer Convolutional Features Edge Detector
3		
5		
7		

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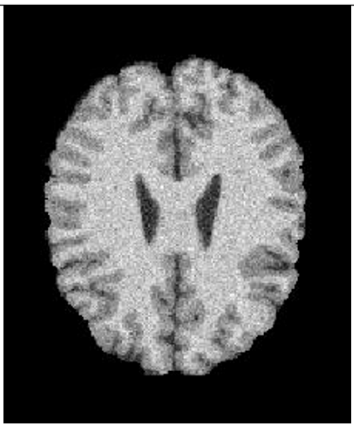
Table 4.6 Results of the Richer Convolutional Features Edge Detector(cont.).

Noise(%)	Original MR Image	Richer Convolutional Features Edge Detector
9		

4.3.3 Results of Bi-Directional Cascade Network Perceptual Edge Detector

Table 4.7 represents the results of Bi-Directional Cascade Network Perceptual edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Bi-Directional Cascade Network Perceptual edge detector degrade as the amount of noise in the MR image dataset is increasing. The Bi-Directional Cascade Network Perceptual edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. Same time it is not able to detect very finer edges in the MR image dataset. It is showing degraded results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs poor in the higher amount of the noise presents in the MR image dataset. These leads inability to detect the finer edges in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Bi-Directional Cascade Network Perceptual edge detector are comparatively improved than that of the traditional edge detectors as well as the Holistically-Nested edge detector and Richer Convolutional Features edge detector of the MR image dataset in the presence of increased amount of the noise.

Table 4.7 Results of the Bi-Directional Cascade Network Perceptual Edge Detector for different noise levels in MR image.

Noise(%)	Original MR Image	Bi-Directional Cascade Network Perceptual Edge Detector
0		
1		

Continue on the next page

Table 4.7 Results of the Bi-Directional Cascade Network Perceptual Edge Detector(cont.).

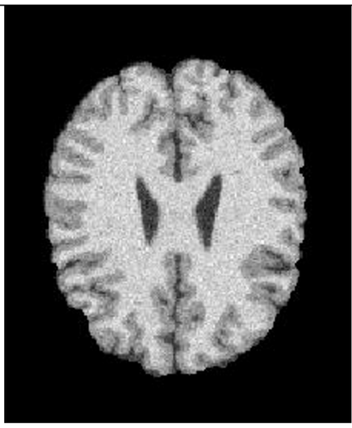
Noise(%)	Original MR Image	Bi-Directional Cascade Network Perceptual Edge Detector
3		
5		
7		

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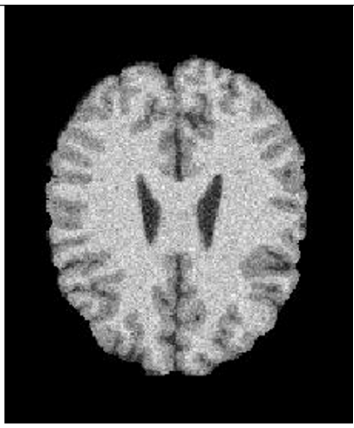
Table 4.7 Results of the Bi-Directional Cascade Network Perceptual Edge Detector(cont.).

Noise(%)	Original MR Image	Bi-Directional Cascade Network Perceptual Edge Detector
9		

4.3.4 Results of Dense Extreme Inception Network Edge Detector

Table 4.8 represents the results of Dense Extreme Inception Network edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Dense Extreme Inception Network edge detector degrade as the amount of noise in the MR image dataset is increasing. The Dense Extreme Inception Network edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. Same time it is not able to detect very finer edges in the MR image dataset. It is showing degraded results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs poor in the higher amount of the noise presents in the MR image dataset. These leads inability to detect the finer edges in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Dense Extreme Inception Network edge detector are comparatively improved than that of the traditional edge detectors as well as the Holistically-Nested edge detector, Richer Convolutional Features edge detector and Bi-Directional Cascade Network Perceptual edge detector of the MR image dataset in the presence of increased amount of the noise.

Table 4.8 Results of the Dense Extreme Inception Network Edge Detector for different noise levels in MR image.

Noise(%)	Original MR Image	Dense Extreme Inception Network Edge Detector
0		
1		

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Table 4.8 Results of the Dense Extreme Inception Network Edge Detector(cont.).

Noise(%)	Original MR Image	Dense Extreme Inception Network Edge Detector
3		
5		
7		

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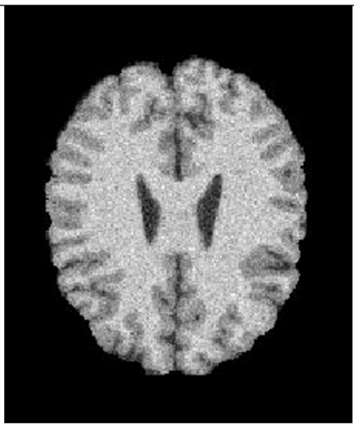
Table 4.8 Results of the Dense Extreme Inception Network Edge Detector(cont.).

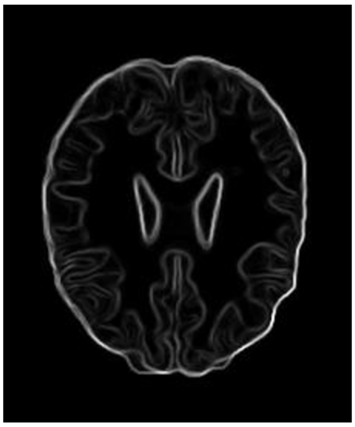
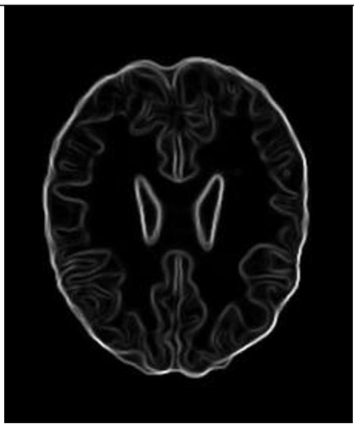
Noise(%)	Original MR Image	Dense Extreme Inception Network Edge Detector
9		

4.4 Results of Bitonic Edge Detector

In this section, the results of proposed Bitonic edge detector on MR image dataset is discussed. After applying the Bitonic edge detector to the MR image dataset, resulting images under various noise levels are obtained.

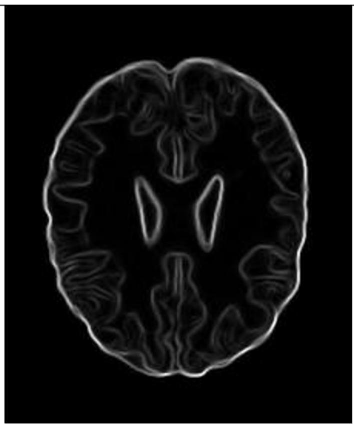
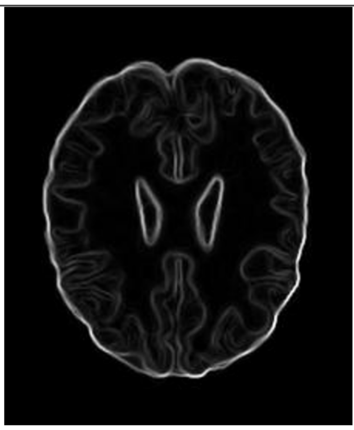
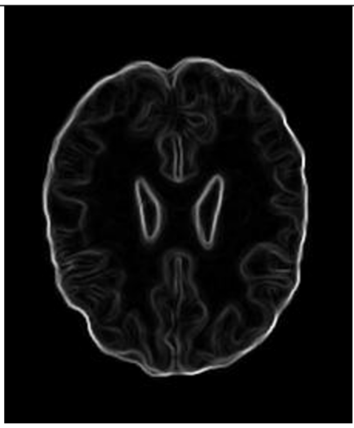
Table 4.9 represents the results of Bitonic edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Bitonic edge detector degrade as the amount of noise in the MR image dataset is increasing. The Bitonic edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. Same time it is also able to detect very finer edges in the MR image dataset. It is showing improved results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs satisfactory in the higher amount of the noise presents in the MR image dataset. These leads better ability to detect the finer edges in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Bitonic edge detector are comparatively improved than that of the traditional edge detectors as well as the state-of-the-art edge detectors of the MR image dataset in the presence of increased amount of the noise.

Table 4.9 Results of the Bitonic Edge Detector for different noise levels in MR image.

Noise(%)	Original MR Image	Bitonic Edge Detector
0		
1		

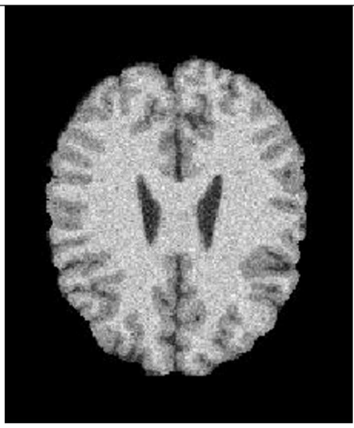
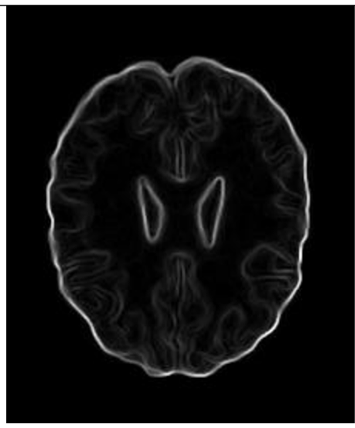
Continue on the next page

Table 4.9 Results of the Bitonic Edge Detector(cont.).

Noise(%)	Original MR Image	Bitonic Edge Detector
3		
5		
7		

Continue on the next page

Table 4.9 Results of the Bitonic Edge Detector(cont.).

Noise(%)	Original MR Image	Bitonic Edge Detector
9		

4.5 Results of Structural Variation Bitonic Edge Detector

In this section, the results of structural variation of the proposed Bitonic edge detector on MR image dataset is discussed. After applying the Structural Variation Bitonic edge detector to the MR image dataset, resulting images under various noise levels are obtained.

Table 4.10 represents the results of Structural Variation Bitonic edge detector on the MR image dataset. here, the noise level in the MR image of the human brain is increased from 0% to 9% of the noise level. It is observed from the resulting images that the result of Structural Variation Bitonic edge detector degrade as the amount of noise in the MR image dataset is increasing. The Structural Variation Bitonic edge detector is able to detect the edges in image when there is no noise or very low amount of noise is in the MR image dataset. Same time it is also able to detect very finer edges in the MR image dataset. It is showing improved results for the edge detector for moderate amount of noise in the MR image dataset. And the edge detector performs satisfactory in the higher amount of the noise presents in the MR image dataset. These leads better ability to detect the finer edges in the MR image dataset because of higher amount of noise present in the MR image dataset.It is observed that the results of the Structural Variation Bitonic edge detector are comparatively improved than that of the traditional edge detectors as well as the state-of-the-art edge detectors and Bitonic of the MR image dataset in the presence of increased amount of the noise.

Table 4.10 Results of the Structural Variation Bitonic Edge Detector for different noise levels in MR image.

Noise(%)	Original MR Image	Structural Variation Bitonic Edge Detector
0		
1		

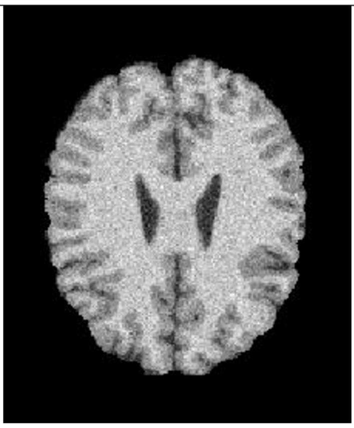
Continue on the next page

Table 4.10 Results of the Structural Variation Bitonic Edge Detector(cont.).

Noise(%)	Original MR Image	Structural Variation Bitonic Edge Detector
3		
5		
7		

Continue on the next page

Table 4.10 Results of the Structural Variation Bitonic Edge Detector(cont.).

Noise(%)	Original MR Image	Structural Variation Bitonic Edge Detector
9		

Chapter 5

Validation and Performance Evaluation of Edge Detectors

This chapter is dedicated to the validation and performance evaluation of the edge detector when applied to MR images. The process involves running the edge detector on the MR image dataset and obtaining resulting images under various noise levels. Subsequently, these results are rigorously validated against a ground truth dataset.

We conduct a comprehensive comparison of the results obtained from different edge detectors against the ground truth dataset. The comparison involves the computation of various performance evaluation measures, including Accuracy and F-measure. This allows us to assess the performance of both traditional and state-of-the-art edge detectors in the context of increasing noise levels.

Furthermore, this chapter also encompasses the performance evaluation of the Proposed Bitonic edge detector and its structural variation, the Bitonic edge detector. The goal is to evaluate their effectiveness in mitigating the impact of noise on edge detection.

5.1 Validation

Validation is of paramount importance in the results of an edge detector applied to an MR image dataset of the human brain. Validation helps assess the accuracy of the detected edges. It allows to determine how well the edge detector is identifying the true boundaries and edges within the brain tissue. This is crucial for ensuring the reliability of subsequent analyses or medical diagnoses that depend on these edges. Different edge detection algorithms may yield different results, and validation helps in comparing their performance. It enables to choose the most suitable algorithm for a specific task or dataset. This is especially important in medical imaging, where the accuracy of edge detection can impact patient diagnosis and treatment planning. Validation allows to evaluate how well the edge detector performs under various noise levels. MRI images can be affected by different types and levels of noise, and understanding how the edge detector responds to noise is essential for robust image analysis. Many edge detection algorithms have adjustable parameters (e.g., threshold values, kernel sizes). Validation helps in fine-tuning these parameters to optimize edge detection results. This ensures that the algorithm is performing at its best on the specific dataset [12, 44].

Validation typically involves comparing the detected edges to a ground truth or manually annotated edges. This ground truth can be created by experts who manually outline brain structures. Comparing the automated results to the ground truth allows you to quantify the algorithm's accuracy and identify any discrepancies. Validation results can indicate how well the edge detector generalizes to different brain images and datasets. This information is valuable for understanding the algorithm's applicability beyond the specific dataset used for training or testing. In scientific research, validation is critical for establishing the credibility of your findings. It demonstrates that o ne methodology is sound and that results are reliable, increasing the trustworthiness of your research within the scientific community. In the context of medical imaging, the validation of edge detection algorithms is crucial for ensuring that the extracted information can be used in clinical settings. Accurate edge detection can aid in the diagnosis and treatment planning of neurological disorders and brain-related conditions. Validation in the results of an edge detector applied to MR images of the human brain is essential for assessing accuracy, robustness, and generalizability. It ensures that the algorithm performs reliably and can be trusted for both research and clinical applications, ultimately contributing to the advancement of medical image analysis and patient care .

It is important to validate the results of edge detectors in brain MR images because edge detectors are often used as a pre-processing step for other image processing tasks, such as segmentation and registration. If the edge detector is not accurate, it can lead to errors in the subsequent tasks [62].

There are a number of different ways to validate the results of edge detectors in brain MR images. One common approach is to use a ground truth image, which is an image that has been manually labeled by an expert. The edge detector output can then be compared to the ground truth image to assess its accuracy .

Another approach to validation is to use a cross-validation scheme. In this approach, the MR image dataset is divided into two sets: a training set and a test set. The edge detector is trained on the training set and then evaluated on the test set. This approach helps to avoid overfitting of the edge detector to the training data [61, 6].

It is important to note that there is no single "best" way to validate the results of edge detectors in brain MR images. The best approach will depend on the specific application and the available resources.

5.2 Performance Evaluation

As MRI images are vital for clinical diagnosis and medical research, ensuring their quality is paramount. Noise in these images can introduce artifacts and reduce the clarity of structures, potentially affecting their diagnostic value. Performance evaluation helps assess the quality of edge detection in noisy MR images. Accurate edge detection is crucial for tasks like tumor detection, lesion localization, and anatomical feature extraction. Noise can lead to false positives or negatives, compromising the diagnostic accuracy. Performance evaluation ensures that edge detectors can provide reliable results under various noise conditions. In medical research, the validity of results is essential. Researchers often use edge detection techniques to analyze brain structures and changes. Reliable performance evaluation ensures that research outcomes are trustworthy, especially when studying diseases or conducting clinical trials. In clinical settings, where MRI plays a pivotal role in patient care, accurate edge detection is essential. It assists in surgical planning, treatment monitoring, and disease progression assessment. Noise can lead to incorrect clinical decisions, making performance evaluation critical.The performance evaluation of edge detectors in the presence of increasing noise can help identify which algorithms or techniques are most robust. This knowledge can guide the selection and optimization of edge detection methods for specific MRI applications. Understanding how edge detectors perform in noisy MRI images can inspire further research and the development of more robust algorithms. It can also lead to innovations in noise reduction techniques, making MRI analysis more reliable. Healthcare institutions and research organizations allocate resources based on the quality and reliability of their tools. Performance evaluation helps ensure that resources are used efficiently, and investments in MRI technology and software yield reliable results.The performance evaluation of edge detectors in the presence of increasing noise is essential for ensuring the reliability, accuracy, and clinical relevance of MRI image analysis, benefiting both medical diagnosis and research in the field of neuroimaging.

5.2.1 Confusion matrix of Classification

A confusion matrix is a square matrix with dimensions $N \times N$, where N is the number of classes or categories in the classification problem. Each row of the matrix represents

Table 5.1 Confusion matrix of Classification

		Ground Truth	
		Positive	Negative
Observed \ Predicted	Positive	TP	FP
	Negative	FN	TN

the instances in an actual (true) or ground truth class, while each column represents the instances in a observed or predicted class [15, 33].

The elements of the Table 5.1 confusion matrix of classification problem represents the following:

$$\begin{aligned} \text{True Positives (TP)} &: \text{Instances correctly predicted as positive} \\ \text{True Negatives (TN)} &: \text{Instances correctly predicted as negative} \\ \text{False Positives (FP)} &: \text{Instances incorrectly predicted as positive (Type I Error)} \\ \text{False Negatives (FN)} &: \text{Instances incorrectly predicted as negative (Type II Error)} \end{aligned}$$

5.2.2 Measures for the Performance Evaluation

Using the components from the confusion matrix in Table 5.1, various performance metrics like Accuracy, Precision, Recall, Specificity and F-measure can be defined.

- **Accuracy** measures the overall correctness of predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision** measures the accuracy of positive predictions:

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall** (Sensitivity or True Positive Rate) measures the ability to capture positive instances:

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **Specificity** (True Negative Rate) measures the ability to capture negative instances:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

- **F-measure** is the harmonic mean of precision and recall, balancing their trade-off:

$$\text{F-measure} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy is easy to understand and interpret. It represents the proportion of correctly classified instances out of the total number of instances. For many stakeholders, including non-technical ones, accuracy provides a clear and intuitive measure of a model's performance. Accuracy gives a broad view of how well the classification model is performing across all classes. It provides a single number that summarizes the model's correctness in making predictions, which is useful for an overall assessment of the model's quality. Accuracy serves as a baseline or reference point for comparing different models or variations of a model. When one develops a new classification algorithm or make changes to an existing one, we can compare their accuracies to determine which one performs better. Accuracy is often used as a quick initial assessment metric. If a model has very high accuracy, it's an indication that it's performing well [15, 33].

The F-measure, which is the harmonic mean of precision and recall, can be a useful metric in the context of an edge detection problem. Edge detection is often a trade-off between detecting as many true edges as possible (high recall) while minimizing the inclusion of false edges (high precision). The F-measure, being the harmonic mean of precision and recall, balances these two conflicting objectives. It helps you find an optimal trade-off between precision and recall, ensuring that both are considered when evaluating the algorithm's performance. In edge detection, both false positives (detecting edges where there are none) and false negatives (missing actual edges) have implications for the quality of the result. The F-measure takes into account both types of errors, giving you a comprehensive view of the algorithm's effectiveness in detecting edges and minimizing errors. The F-measure provides a single value that quantifies the quality of edge detection, making it easier to compare different edge detection algorithms or parameter settings. It encapsulates the algorithm's ability to identify edges accurately while avoiding spurious edge detection [15, 33, 51].

The application of the confusion matrix and performance metrics like Accuracy, Precision, Recall, Specificity and F-measure are discussed in details in [45, 59, 20, 25].

5.3 Performance Evaluation of Traditional Edge Detectors

5.3.1 Performance Evaluation of Roberts Edge Detector

Accuracy of Roberts Edge Detector

Figure 5.1 illustrates the relationship between the accuracy of the Roberts edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the accuracy of the Roberts edge detector, quantified as the percentage of correctly identified edges among the entire set of detected edges.The graph's compelling insight is the pronounced decline in accuracy as the noise levels escalate. This finding underscores the limited robustness of the Roberts edge detector in the presence of noise, as its accuracy diminishes significantly under such conditions. Furthermore, it's worth noting that the observed trend is nonlinear, indicating that the accuracy's descent is not uniform across different noise levels. In fact, the graph exhibits a concave downward shape, signifying that the rate of accuracy decline accelerates as noise levels increase. This heightened sensitivity to noise suggests that alternative edge detection methods may be necessary when dealing with noisy MR image datasets. The Roberts edge detector's performance is notably affected by noise in the MR image dataset, as evidenced by the graph's trends. Its limited robustness underscores the importance of considering noise-reduction techniques or alternative detectors for improved accuracy in such scenarios.

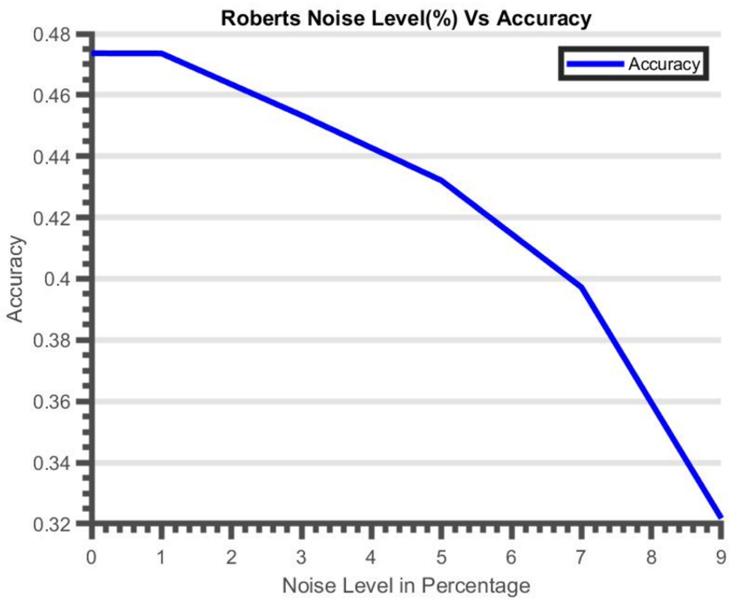


Fig. 5.1 The impact of noise on the accuracy of Roberts edge detector in MR image

F-measure of Roberts Edge Detector

Figure 5.2 illustrates the relationship between the F-measure of the Roberts edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Roberts edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector. The F-measure of the Roberts edge detector decreases with increasing noise level. This suggests that the Roberts edge detector is not very robust to noise. At a noise level of 0%, the F-measure of the Roberts edge detector is relatively low. At a noise level of 9%, the F-measure of the Roberts edge detector is very low. A decrease in the F-measure with increasing noise levels is expected. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a lower F-measure. This decrease in F-measure suggests that the ability of Roberts edge detector to accurately detect edges deteriorates as noise is introduced into the image. This decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image.

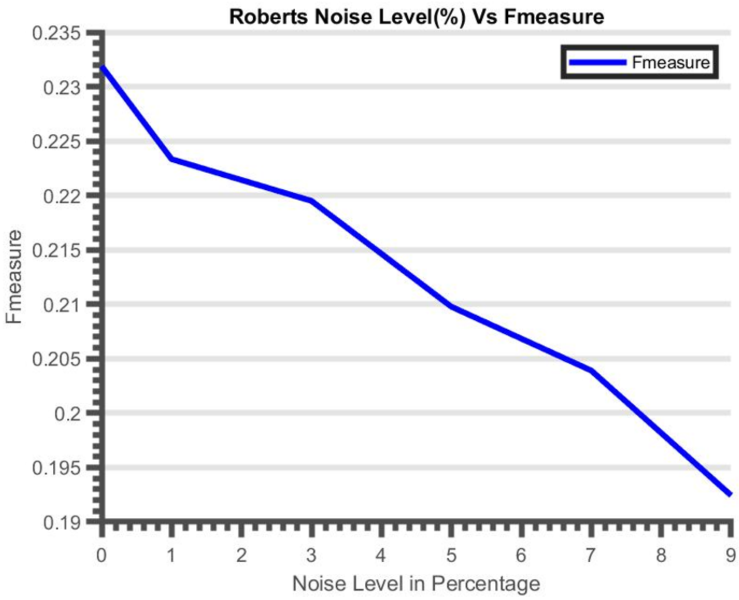


Fig. 5.2 The impact of noise on the F-measure of Roberts edge detector in MR image

5.3.2 Performance Evaluation of Prewitt Edge Detector

Accuracy of Prewitt Edge Detector

Figure 5.3 illustrates the relationship between the accuracy of the Prewitt edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the accuracy of the Prewitt edge detector, quantified as the percentage of correctly identified edges among the entire set of detected edges.The graph's compelling insight is the pronounced decline in accuracy as the noise levels escalate. This finding underscores the limited robustness of the Prewitt edge detector in the presence of noise, as its accuracy diminishes significantly under such conditions. Furthermore, it's worth noting that the observed trend is nonlinear, indicating that the accuracy's descent is not uniform across different noise levels. In fact, the graph exhibits a concave downward shape, signifying that the rate of accuracy decline accelerates as noise levels increase. This heightened sensitivity to noise suggests that alternative edge detection methods may be necessary when dealing with noisy MR image datasets. The Prewitt edge detector's performance is notably affected by noise and shows improved than Roberts edge detector in the MR image dataset, as evidenced by the graph's trends. Its limited robustness underscores the importance of considering noise-reduction techniques or alternative detectors for improved accuracy in such scenarios.

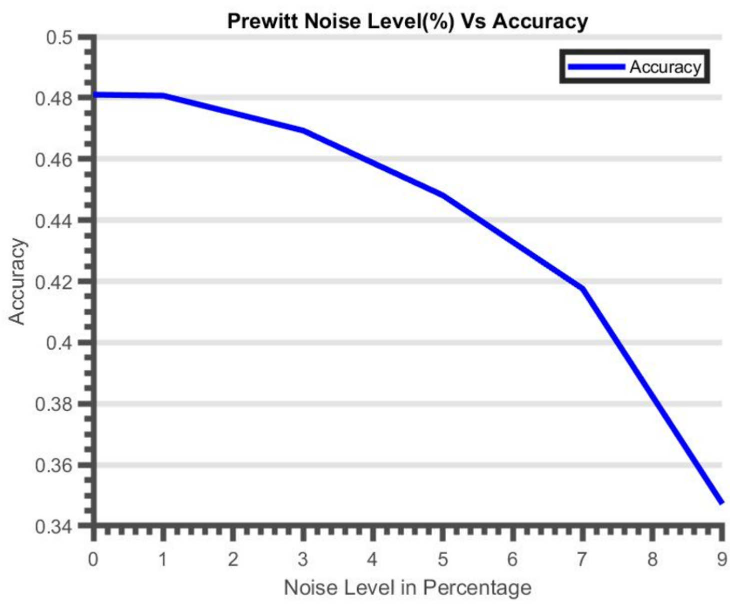


Fig. 5.3 The impact of noise on the accuracy of Prewitt edge detector in MR image

F-measure of Prewitt Edge Detector

Figure 5.4 illustrates the relationship between the F-measure of the Prewitt edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Prewitt edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector. The F-measure of the

Prewitt edge detector decreases with increasing noise level. This suggests that the Prewitt edge detector is not very robust to noise. At a noise level of 0%, the F-measure of the Prewitt edge detector is relatively low. At a noise level of 9%, the F-measure of the Prewitt edge detector is very low. A decrease in the F-measure with increasing noise levels is expected. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a lower F-measure. This decrease in F-measure suggests that the ability of Prewitt edge detector to accurately detect edges deteriorates as noise is introduced into the image. This decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Prewitt edge detector are improved than that of the Roberts edge detector.

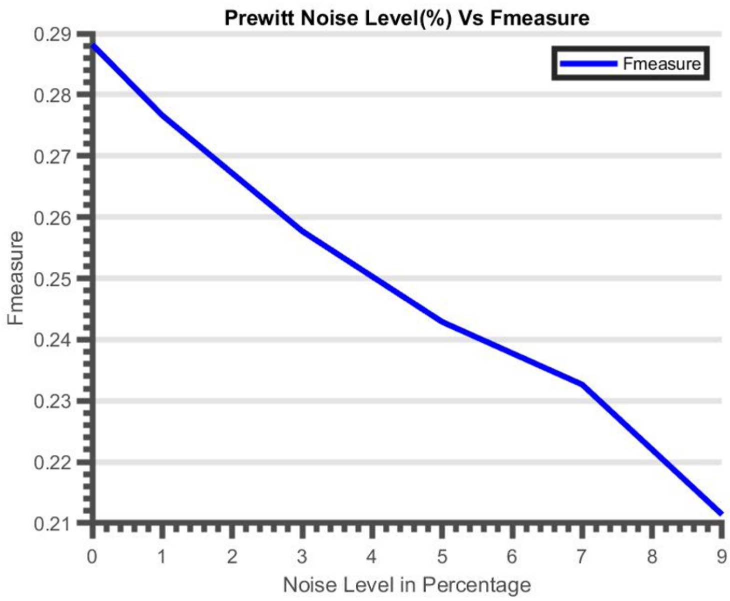


Fig. 5.4 The impact of noise on the F-measure of Prewitt edge detector in MR image

5.3.3 Performance Evaluation of Sobel-Feldman Edge Detector

Accuracy Sobel-Feldman Edge Detector

Figure 5.5 illustrates the relationship between the accuracy of the Sobel-Feldman edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the accuracy of the Sobel-Feldman edge detector, quantified as the percentage of correctly identified edges among the entire set of detected edges.The graph's compelling insight is the pronounced decline in accuracy as the noise levels escalate. This finding underscores the limited robustness of the Sobel-Feldman edge detector in the presence of noise, as its accuracy diminishes significantly under such conditions. Furthermore, it's worth noting that the observed trend is nonlinear, indicating that the accuracy's descent is not uniform across different noise levels. In fact, the graph exhibits a concave downward shape, signifying that the rate of accuracy decline accelerates as noise levels increase. This heightened sensitivity to noise suggests that alternative edge detection methods may be necessary when dealing with noisy MR image datasets. The Sobel-Feldman edge detector's performance is notably affected by noise and shows improved than Roberts and Prewitt edge detector in the MR image dataset, as evidenced by the graph's trends. Its limited robustness underscores the importance of considering noise-reduction techniques or alternative detectors for improved accuracy in such scenarios.

F-measure Sobel-Feldman Edge Detector

Figure 5.6 illustrates the relationship between the F-measure of the Sobel-Feldman edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Sobel-Feldman edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector. The F-measure of the Sobel-Feldman edge detector decreases with increasing noise level. This suggests that the Sobel-Feldman edge detector is not very robust to noise. At a noise level

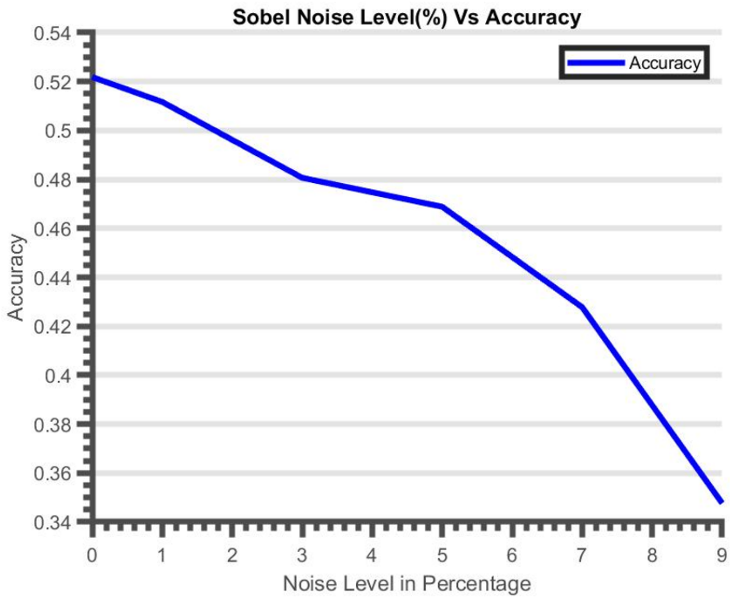


Fig. 5.5 The impact of noise on the accuracy of Sobel-Feldman edge detector in MR image

of 0%, the F-measure of the Sobel-Feldman edge detector is relatively low. At a noise level of 9%, the F-measure of the Sobel-Feldman edge detector is very low. A decrease in the F-measure with increasing noise levels is expected. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a lower F-measure. This decrease in F-measure suggests that the ability of Sobel-Feldman edge detector to accurately detect edges deteriorates as noise is introduced into the image. This decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Sobel-Feldman edge detector are improved than that of the Roberts edge detector and the Prewitt edge detector.

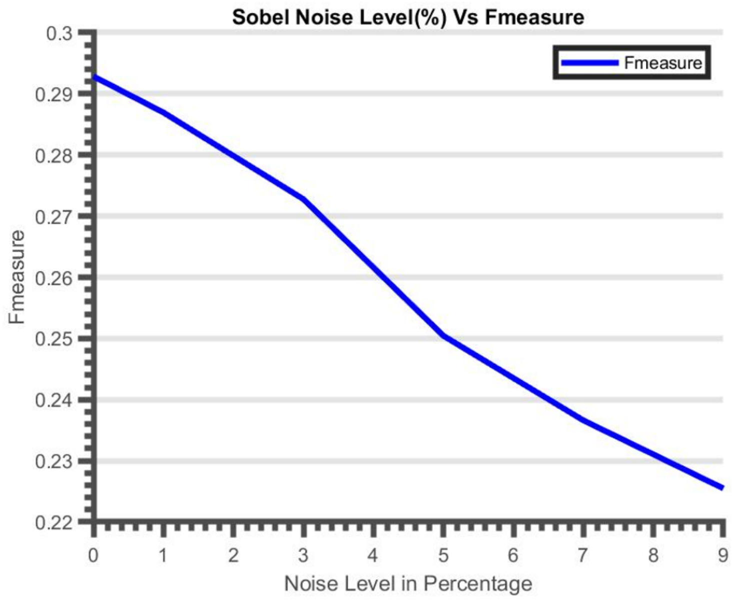


Fig. 5.6 The impact of noise on the F-measure of Sobel-Feldman edge detector in MR image

5.4 Performance Evaluation of State-of-the-Art Edge Detectors

5.4.1 Performance Evaluation of Holistically-Nested Edge Detector

Accuracy of Holistically-Nested Edge Detector

Figure 5.7 illustrates the relationship between the accuracy of the Holistically-Nested edge detector and varying levels of noise within the MR image dataset. The y-axis represents the accuracy of the Holistically-Nested edge detector, quantified as the percentage of correctly identified edges among all detected edges. The graph reveals a significant trend — a notable decrease in accuracy as the noise levels increase. This observation highlights the improved, albeit limited, robustness of the Holistically-Nested edge detector in the presence of noise. Its accuracy diminishes progressively under such conditions. It's important to note that the observed trend is nonlinear, indicating that the decline in accuracy is not uniform across different noise levels. In fact, the graph takes on a convex upward shape, suggesting that the rate of accuracy decline slows down as noise levels increase. This reduced sensitivity to noise implies that alternative edge detection methods may be more suitable when working with noisy MR image datasets. The performance of the Holistically-Nested edge detector is affected by noise, although it exhibits improved performance compared to traditional edge detectors in the MR image dataset, as indicated by the graph's trends. Its enhanced but still affected robustness emphasizes the need to explore noise-reduction techniques or consider alternative detectors for achieving improved accuracy in such scenarios.

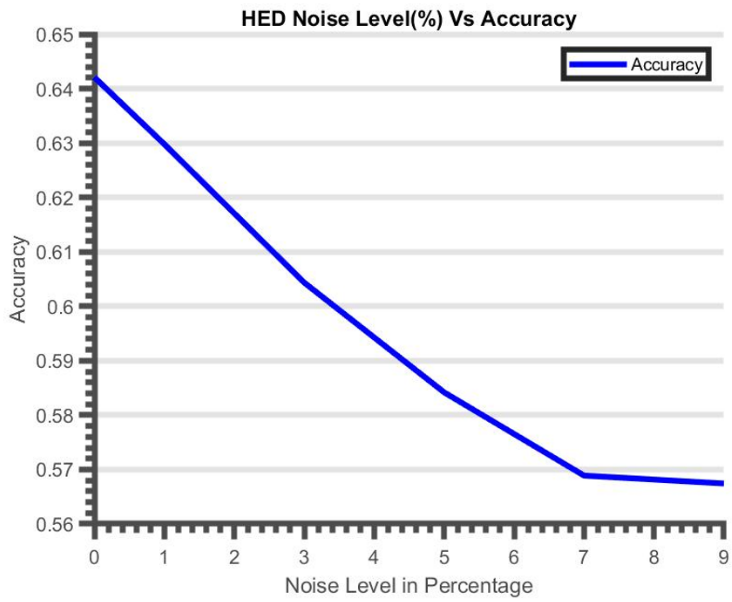


Fig. 5.7 The impact of noise on the accuracy of Holistically-Nested edge detector in MR image

F-measure of Holistically-Nested Edge Detector

Figure 5.8 illustrates the relationship between the F-measure of the Holistically-Nested edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Holistically-Nested edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector.

The F-measure of the Holistically-Nested edge detector decreases with increasing noise level. This suggests that the Holistically-Nested edge detector is not very robust to noise. At a noise level of 0%, the F-measure of the Holistically-Nested edge detector is relatively high. At a noise level of 9%, the F-measure of the Holistically-Nested edge detector is relatively low. A decrease in the F-measure with increasing noise levels is expected. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a decrease in F-measure. This decrease in F-measure suggests that the ability of Holistically-Nested edge detector to accurately detect edges deteriorates as noise is introduced into the image. This decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Holistically-Nested edge detector are improved than that of the traditional edge detectors.

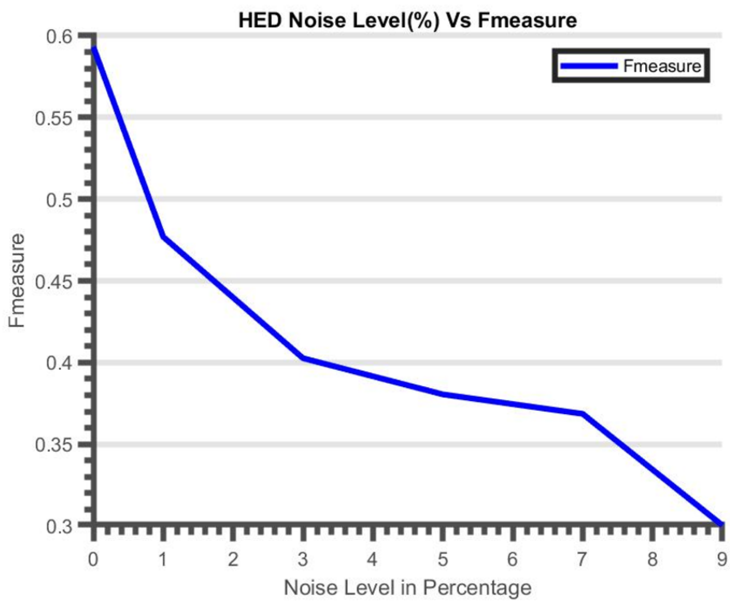


Fig. 5.8 The impact of noise on the F-measure of Holistically-Nested edge detector in MR image

5.4.2 Performance Evaluation of Richer Convolutional Features Edge Detector

Accuracy of Richer Convolutional Features Edge Detector

Figure 5.9 illustrates the relationship between the accuracy of the Richer Convolutional Features and varying levels of noise within the MR image dataset. The y-axis represents the accuracy of the Richer Convolutional Features, quantified as the percentage of correctly identified edges among all detected edges. The graph reveals a significant trend — a notable decrease in accuracy as the noise levels increase. This observation highlights the improved, albeit limited, robustness of the Richer Convolutional Features in the presence of noise. Its accuracy diminishes progressively under such conditions. It's important to note that the observed trend is nonlinear, indicating that the decline in accuracy is not uniform across different noise levels. In fact, the graph takes on a convex upward shape, suggesting that the rate of accuracy decline slows down as noise levels increase. This reduced sensitivity to noise implies that alternative edge detection methods may be more suitable when working with noisy MR image datasets. The performance of the Richer Convolutional Features is affected by noise, although it exhibits improved performance compared to traditional edge detectors and Holistically-Nested edge detector in the MR image dataset, as indicated by the graph's trends. Its enhanced but still affected robustness emphasizes the need to explore noise-reduction techniques or consider alternative detectors for achieving improved accuracy in such scenarios.

F-measure of Richer Convolutional Features Edge Detector

Figure 5.10 illustrates the relationship between the F-measure of the Richer Convolutional Features edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Richer Convolutional Features edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance

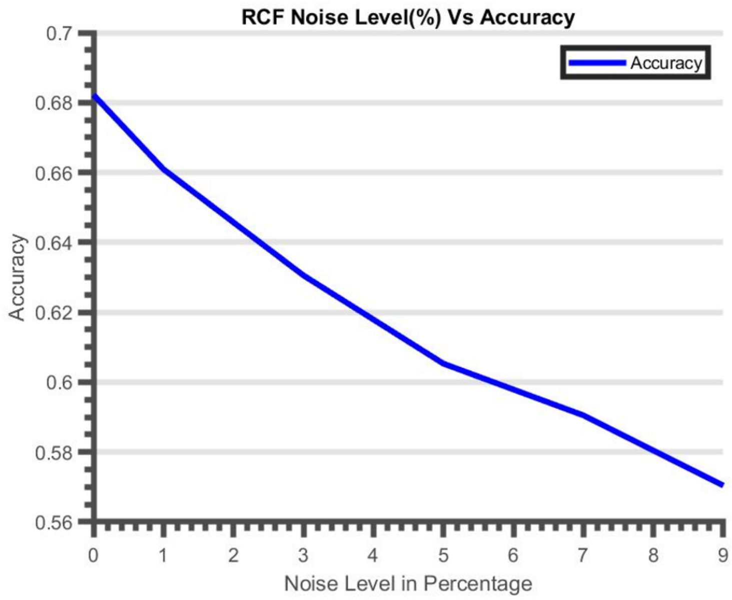


Fig. 5.9 The impact of noise on the accuracy of Richer Convolutional Features edge detector in MR image

for edge detector. The F-measure of the Richer Convolutional Features edge detector decreases with increasing noise level. This suggests that the Richer Convolutional Features edge detector is not very robust to noise. At a noise level of 0%, the F-measure of the Richer Convolutional Features edge detector is relatively high. At a noise level of 9%, the F-measure of the Richer Convolutional Features edge detector is relatively low. A decrease in the F-measure with increasing noise levels is expected. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a decrease in F-measure. This decrease in F-measure suggests that the ability of Richer Convolutional Features to accurately detect edges deteriorates as noise is introduced into the image. This decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Richer Convolutional Features edge detector are improved than that of the traditional edge detectors and the Holistically-Nested edge detector.

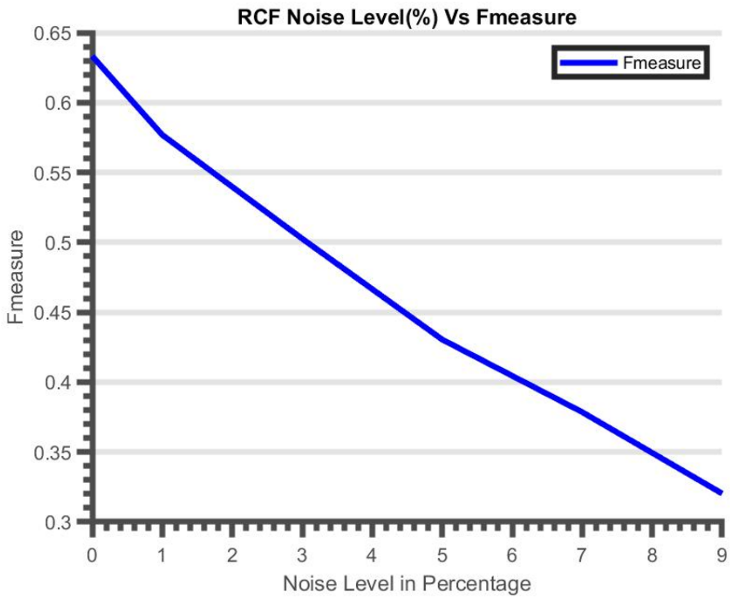


Fig. 5.10 The impact of noise on the F-measure of Richer Convolutional Features edge detector in MR image

5.4.3 Performance Evaluation of Bi-Directional Cascade Network Perceptual Edge Detector

Accuracy of Bi-Directional Cascade Network Perceptual Edge Detector

Figure 5.11 illustrates the relationship between the accuracy of the Bi-Directional Cascade Network Perceptual edge detector and varying levels of noise within the MR image dataset. The y-axis represents the accuracy of the Bi-Directional Cascade Network Perceptual edge detector, quantified as the percentage of correctly identified edges among all detected edges. The graph reveals a significant trend — a notable decrease in accuracy as the noise levels increase. This observation highlights the improved, albeit limited, robustness of the Bi-Directional Cascade Network Perceptual edge detector in the presence of noise. Its accuracy diminishes progressively under such conditions. It's important to note that the observed trend is nonlinear, indicating that the decline in accuracy is not uniform across different noise levels. In fact, the graph takes on a convex upward shape, suggesting that the rate of accuracy decline slows down as noise levels increase. This reduced sensitivity to noise implies that alternative edge detection methods may be more suitable when working with noisy MR image datasets. The performance of the Bi-Directional Cascade Network Perceptual edge detector is affected by noise, although it exhibits improved performance compared to traditional edge detectors, Holistically-Nested edge detector and Richer Convolutional Features edge detector in the MR image dataset, as indicated by the graph's trends. Its enhanced but still affected robustness emphasizes the need to explore noise-reduction techniques or consider alternative detectors for achieving improved accuracy in such scenarios.

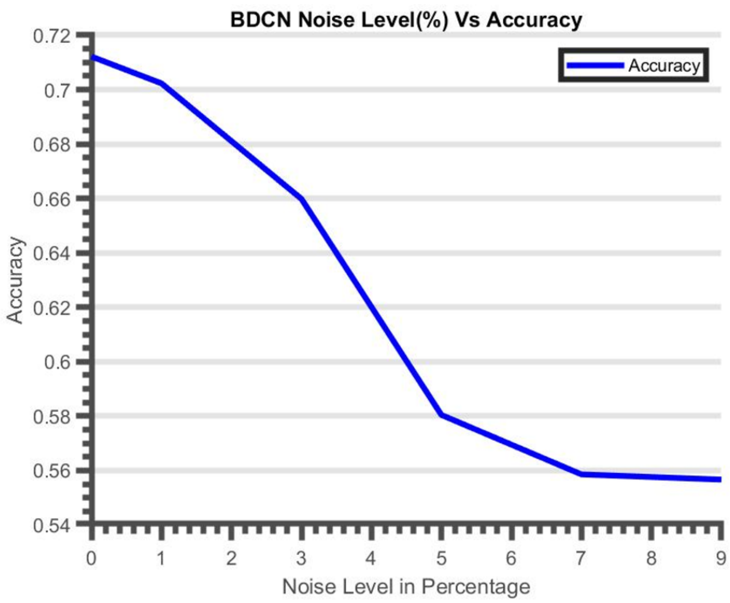


Fig. 5.11 The impact of noise on the accuracy of Bi-Directional Cascade Network Perceptual edge detector in MR image

F-measure of Bi-Directional Cascade Network Perceptual Edge Detector

Figure 5.12 illustrates the relationship between the F-measure of the Bi-Directional Cascade Network Perceptual edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Bi-Directional Cascade Network Perceptual edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector. The F-measure of the Bi-Directional

Cascade Network Perceptual edge detector decreases with increasing noise level. This suggests that the Bi-Directional Cascade Network Perceptual edge detector is not very robust to noise. At a noise level of 0%, the F-measure of the Bi-Directional Cascade Network Perceptual edge detector is relatively high. At a noise level of 9%, the F-measure of the Bi-Directional Cascade Network Perceptual edge detector is relatively low. A decrease in the F-measure with increasing noise levels is expected. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a decrease in F-measure. This decrease in F-measure suggests that the ability of Bi-Directional Cascade Network Perceptual to accurately detect edges deteriorates as noise is introduced into the image. This decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Bi-Directional Cascade Network Perceptual edge detector are improved than that of the traditional edge detectors, the Holistically-Nested edge detector and Richer Convolutional Features edge detector.

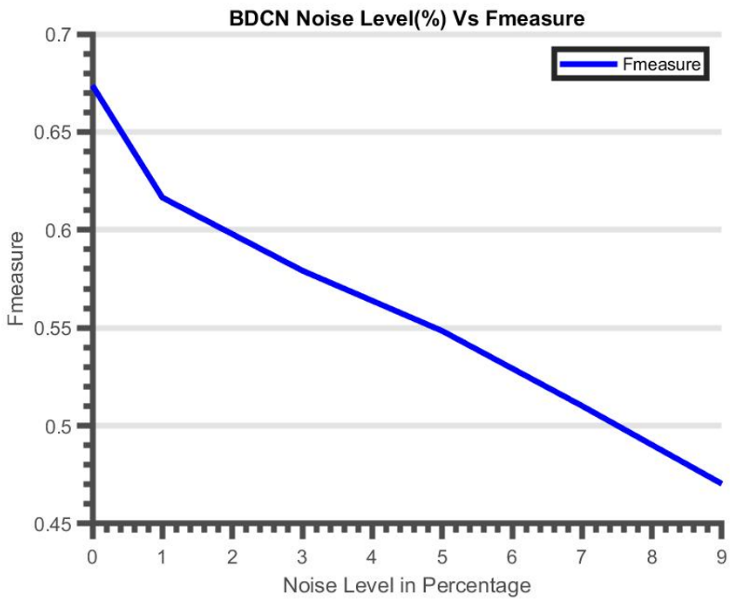


Fig. 5.12 The impact of noise on the F-measure of Bi-Directional Cascade Network Perceptual edge detector in MR image

5.4.4 Performance Evaluation of Dense Extreme Inception Network Edge Detector

Accuracy of Dense Extreme Inception Network Edge Detector

Figure 5.13 illustrates the relationship between the accuracy of the Dense Extreme Inception Network edge detector and varying levels of noise within the MR image dataset. The y-axis represents the accuracy of the Dense Extreme Inception Network edge detector, quantified as the percentage of correctly identified edges among all detected edges. The graph reveals a significant trend — a notable decrease in accuracy as the noise levels increase. This observation highlights the improved, albeit limited, robustness of the Dense Extreme Inception Network edge detector in the presence of noise. Its accuracy diminishes progressively under such conditions. It's important to note that the observed trend is nonlinear, indicating that the decline in accuracy is not uniform across different noise levels. In fact, the graph takes on a convex upward shape, suggesting that the rate of accuracy decline slows down as noise levels increase. This reduced sensitivity to noise implies that alternative edge detection methods may be more suitable when working with noisy MR image datasets. The performance of the Dense Extreme Inception Network edge detector is affected by noise, although it exhibits improved performance compared to traditional edge detectors, Holistically-Nested edge detector, Richer Convolutional Features edge detector and Bi-Directional Cascade Network Perceptual edge detector in the MR image dataset, as indicated by the graph's trends. Its enhanced but still affected robustness emphasizes the need to explore noise-reduction techniques or consider alternative detectors for achieving improved accuracy in such scenarios.

F-measure of Dense Extreme Inception Network Edge Detector

Figure 5.14 illustrates the relationship between the F-measure of the Dense Extreme Inception Network edge detector and varying noise levels within the MR image dataset.

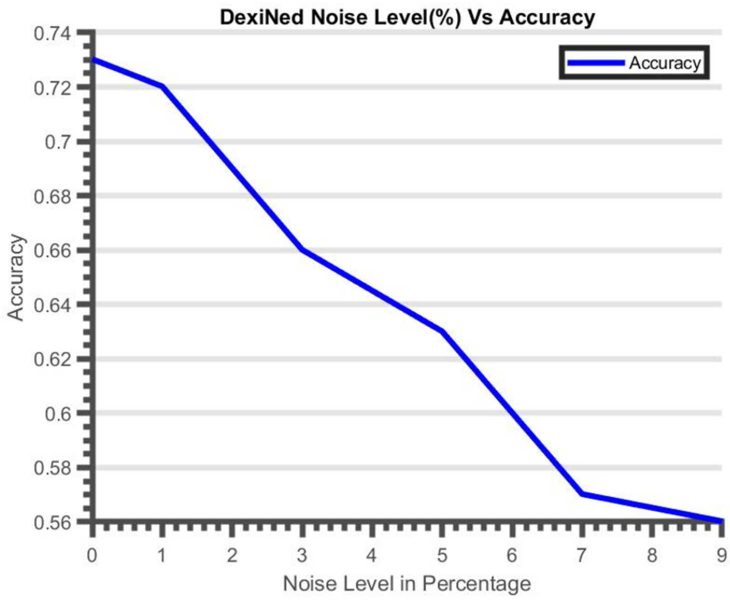


Fig. 5.13 The impact of noise on the accuracy of Dense Extreme Inception Network edge detector in MR image

On the y-axis, we depict the F-measure of the Dense Extreme Inception Network edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector. The F-measure of the Dense Extreme Inception Network edge detector decreases with increasing noise level. This suggests that the Dense Extreme Inception Network edge detector is not very robust to noise. At a noise level of 0%, the F-measure of the Dense Extreme Inception Network edge detector is relatively high. At a noise level of 9%, the F-measure of the Dense Extreme Inception Network edge detector is relatively low. A decrease in the F-measure with increasing noise levels is expected. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a decrease in F-measure. This decrease in F-measure suggests that the ability of Dense Extreme Inception Network to accurately detect edges deteriorates as noise is introduced into the image. This decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Dense Extreme Inception

Network edge detector are improved than that of the traditional edge detectors, the Holistically-Nested edge detector, Richer Convolutional Features edge detector and Bi-Directional Cascade Network Perceptual edge detector.

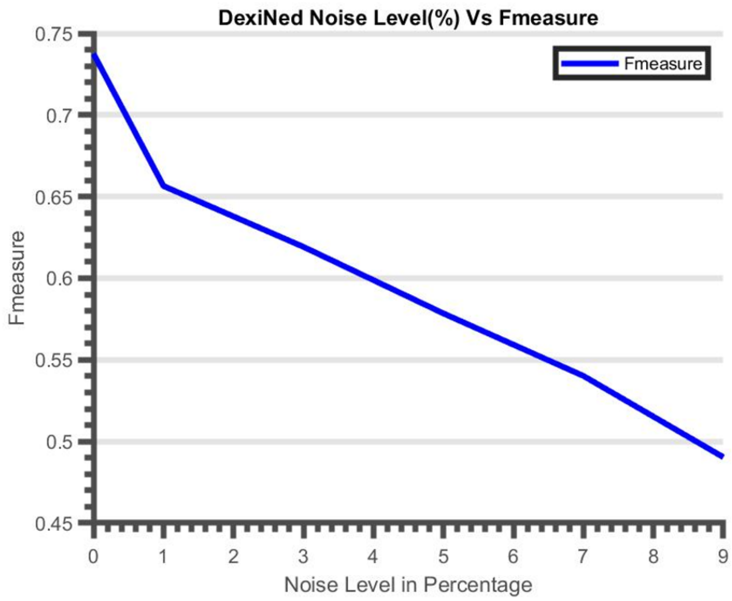


Fig. 5.14 The impact of noise on the F-measure of Dense Extreme Inception Network edge detector in MR image

5.5 Performance Evaluation of Bitonic Edge Detector

Accuracy of Bitonic Edge Detector

Figure 5.15 visually represents the interplay between the accuracy of the Bitonic edge detector and varying levels of noise within the MR image dataset. The y-axis represents the accuracy of the Bitonic edge detector, quantified as the percentage of correctly identified edges among all detected edges. Notably, the graph reveals an intriguing trend — a slight decrease in accuracy as noise levels increase. This observation underscores the Bitonic edge detector's commendable robustness when confronted with noise. Its accuracy experiences a marginal dip in such conditions. Crucially, this observed trend is non-linear, indicating that the slight decrease in accuracy is not uniform across different noise levels.

In fact, the graph assumes a convex upward shape, implying that the rate of accuracy decline decelerates as noise levels rise. This reduced slight sensitivity to noise suggests that, when operating with noisy MR image datasets, Bitonic edge detection methods may be more suitable. Comparatively, the Bitonic edge detector's performance in the presence of noise is slightly affected, yet it outperforms traditional edge detectors and the Holistically-Nested edge detector, Richer Convolutional Features edge detector, Bi-Directional Cascade Network Perceptual edge detector, and Dense Extreme Inception Network edge detector within the MR image dataset, as evidenced by the trends depicted in the graph. Its improved robustness makes the Bitonic edge detector important for edge detection in the MR image dataset in the presence of noise.

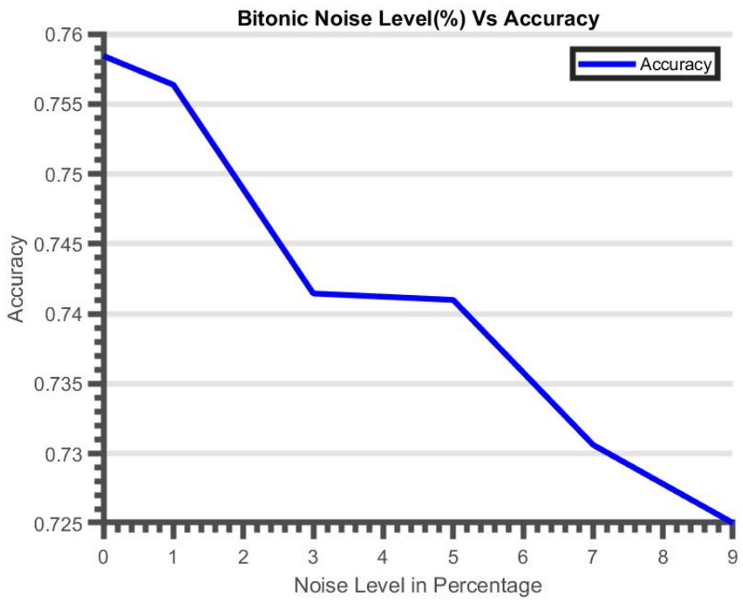


Fig. 5.15 The impact of noise on the accuracy of Bitonic edge detector in MR image

F-measure of Bitonic Edge Detector

Figure 5.16 illustrates the relationship between the F-measure of the Bitonic edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Bitonic edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector. The F-measure of the Bitonic edge detector slightly decreases with increasing noise level. This suggests that the Bitonic edge detector is very robust to noise. At a noise level of 0%, the F-measure of the Bitonic edge detector is relatively high. At a noise level of 9%, the F-measure of the Bitonic edge detector is slightly low. A very less decrease in the F-measure with increasing noise levels is observed. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a slight decrease in F-measure. This decrease in F-measure suggests that the ability of Bitonic to accurately detect edges deteriorates as noise is introduced into the image. This slight decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Bitonic edge detector are improved than that of the traditional edge detectors, the Holistically-Nested edge detector, Richer Convolutional Features edge detector, Bi-Directional Cascade Network Perceptual edge detector and Dense Extreme Inception Network edge detector. Its improved robustness makes the Bitonic edge detector important for edge detection in the MR image dataset in the presence of noise.

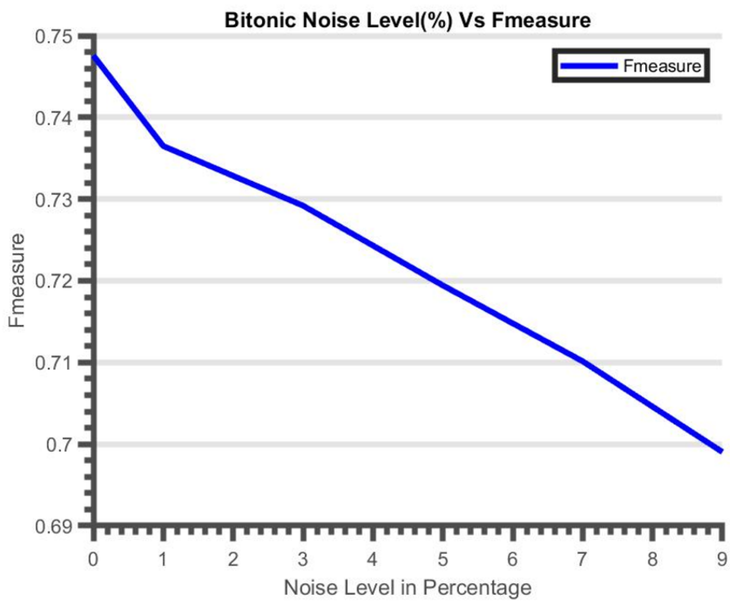


Fig. 5.16 The impact of noise on the F-measure of Bitonic edge detector in MR image

5.6 Performance Evaluation of Structural Variation Bitonic Edge Detector

Accuracy of Structural Variation Bitonic Edge Detector

Figure 5.15 visually represents the interplay between the accuracy of the Structural Variation Bitonic edge detector and varying levels of noise within the MR image dataset. The y-axis represents the accuracy of the Structural Variation Bitonic edge detector, quantified as the percentage of correctly identified edges among all detected edges. Notably, the graph reveals an intriguing trend — a slight decrease in accuracy as noise levels increase. This observation underscores the Structural Variation Bitonic edge detector's commendable robustness when confronted with noise. Its accuracy experiences a marginal dip in such conditions. Crucially, this observed trend is non-linear, indicating that the slight decrease in accuracy is not uniform across different noise levels. In fact, the graph assumes a convex upward shape, implying that the rate of accuracy decline decelerates as noise levels rise. This reduced slight sensitivity to noise suggests that, when operating with noisy MR image datasets, Structural Variation Bitonic edge detection methods may be more suitable. Comparatively, the Structural Variation Bitonic edge detector's performance in the presence of noise is slightly affected, yet it outperforms traditional edge detectors and the Holistically-Nested edge detector, Richer Convolutional Features edge detector, Bi-Directional Cascade Network Perceptual edge detector, and Dense Extreme Inception Network edge detector and Bitonic edge detector within the MR image dataset, as evidenced by the trends depicted in the graph. Its improved robustness makes the Structural Variation Bitonic edge detector important for edge detection in the MR image dataset in the presence of noise.

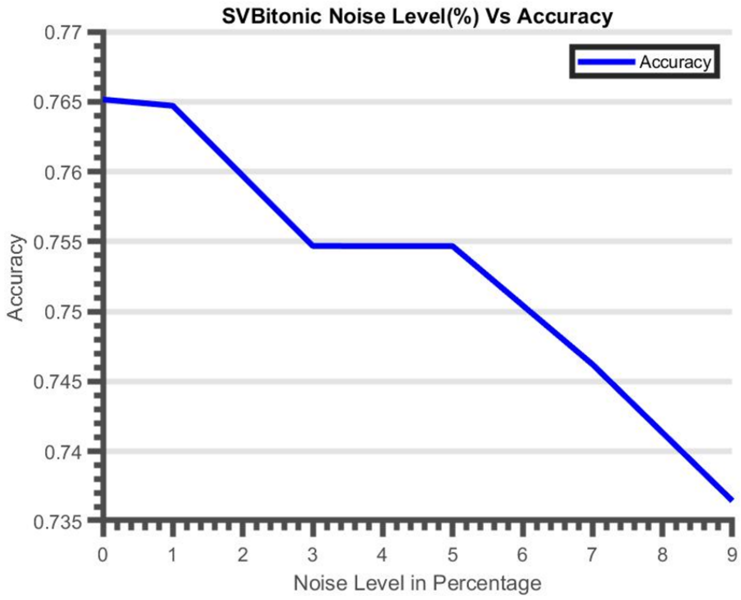


Fig. 5.17 The impact of noise on the accuracy of Structural Variation Bitonic edge detector in MR image

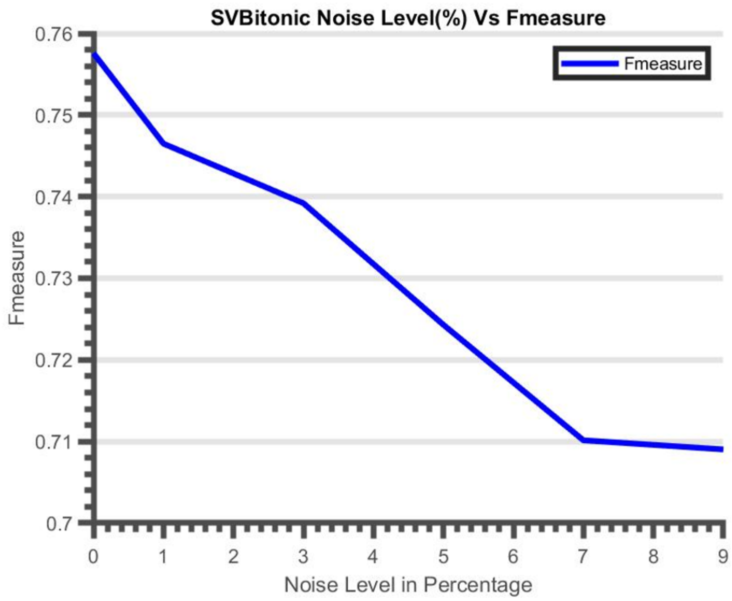


Fig. 5.18 The impact of noise on the F-measure of Structural Variation Bitonic edge detector in MR image

F-measure of Structural Variation Bitonic Edge Detector

Figure 5.18 illustrates the relationship between the F-measure of the Structural Variation Bitonic edge detector and varying noise levels within the MR image dataset. On the y-axis, we depict the F-measure of the Structural Variation Bitonic edge detector, combines the precision and recall into a single metric to provide a balanced measure of performance for edge detector. The F-measure of the Structural Variation Bitonic edge detector slightly decreases with increasing noise level. This suggests that the Structural Variation Bitonic edge detector is very robust to noise. At a noise level of 0%, the F-measure of the Structural Variation Structural Variation Bitonic edge detector is relatively high. At a noise level of 9%, the F-measure of the Structural Variation Bitonic edge detector is slightly low. A very less decrease in the F-measure with increasing noise levels is observed. Noise can introduce spurious edges or blur existing edges, making edge detection more challenging. As the noise level increases, it becomes harder for the algorithm to distinguish between genuine edges and noise-induced artifacts. Consequently, both precision and recall tend to decrease, leading to a slight decrease in F-measure. This decrease in F-measure suggests that the ability of Structural Variation Bitonic to accurately detect edges deteriorates as noise is introduced into the image. This slight decrease in F-measure suggests that the algorithm's ability to accurately detect edges deteriorates as noise is introduced into the image. It is observed that the F-measure values of the Structural Variation Bitonic edge detector are improved than that of the traditional edge detectors, the Holistically-Nested edge detector, Richer Convolutional Features edge detector, Bi-Directional Cascade Network Perceptual edge detector and Dense Extreme Inception Network edge detector and Bitonic edge detector. Its improved robustness makes the Structural Variation Bitonic edge detector important for edge detection in the MR image dataset in the presence of noise.

Chapter 6

Conclusion and Future Scope

In Chapter 6, we draw conclusions regarding the performance of edge detectors in the presence of increasing noise levels. This chapter encapsulates the key findings and insights gathered from the previous chapters, shedding light on the effectiveness of edge detection techniques under varying noise conditions. Furthermore, we explore the future scope and potential directions for further research and development in this area within the same chapter.

6.1 Conclusion

In our comprehensive study, we undertook a rigorous investigation to enhance the accuracy and F-measure of edge detection in magnetic resonance (MR) image datasets, particularly in the presence of escalating levels of noise. This endeavor is of paramount importance in the realm of medical image analysis, where edge detection serves as a fundamental tool for various clinical applications. The ability to accurately detect edges in MR images is crucial for tasks such as delineating anatomical structures, localizing pathologies, and characterizing diseases. However, the challenge of noise in MR images has long been acknowledged as a significant obstacle. Noise can severely impair the performance of edge detection algorithms, compromising their precision and recall. By improving the robustness of edge detection algorithms in the presence of noise, we aim to enhance the overall accuracy and F-measure of medical image analysis. This, in turn, can lead to more precise clinical diagnoses and more effective treatment plans. Our study represents a significant step forward in the field of medical imaging, with the potential to improve patient outcomes and advance the practice of medicine.

Through a meticulous examination of both traditional and state-of-the-art edge detection algorithms, we conducted a thorough investigation into their performance when applied to MR image datasets in the presence of varying levels of noise. This detailed analysis has not only provided a comprehensive understanding of existing methodologies but has also allowed us to identify key areas for improvement. Our research has contributed novel insights and advanced methodologies to address the challenges posed by noise in MR image analysis. By delving deeply into the performance measurement of these edge detectors, we have been able to their accuracy and F-measure in noisy environments. These contributions are poised to have a significant impact on the field, offering new approaches to improve the detection of edges in MR images and thus advancing the capabilities of medical image analysis. Throughout our research endeavors, several key findings have emerged, highlighting the importance of robust edge detection algorithms in clinical applications. These findings have important implications for the future of edge detection in MR image analysis, paving the way for the development of more effective and reliable tools for medical professionals.

Our investigations have confirmed the inherent sensitivity of widely used traditional edge detectors, such as the Roberts edge detector, Prewitt edge detector, and Sobel-Feldman edge detector, to varying levels of noise within MR image datasets. Additionally, we explored the performance of state-of-the-art edge detectors, including the Holistically-Nested edge detector, Richer Convolutional Features edge detector, Bi-Directional Cascade Network Perceptual edge detector, and Dense Extreme Inception Network edge detector, under similar conditions. Our findings revealed a significant decline in accuracy and

F-measure as noise levels increased. This sensitivity to noise underscores the need for tailored solutions that can preserve edge detection accuracy in the presence of noise. These results highlight the challenges faced by existing edge detection algorithms when applied to noisy MR image datasets and emphasize the importance of developing robust algorithms that can effectively handle noise while maintaining high levels of accuracy. This thesis makes a significant contribution to the field of medical image analysis by introducing a novel and robust edge detector specifically designed to operate effectively in the presence of noise in magnetic resonance (MR) images. The proposed Bitonic edge detector represents a pioneering approach, offering a new benchmark for the development of future noise-robust edge detection algorithms in the presence of noise in magnetic resonance (MR) images.

By addressing the challenges posed by noise in MR images, the Bitonic edge detector opens up new possibilities for improving the accuracy and F-measure of edge detection in medical imaging. Its effectiveness in noisy environments pave the way for the development of more advanced and noise-robust edge detection techniques in the presence of noise in magnetic resonance (MR) images, ultimately leading to enhanced diagnostic capabilities and improved patient care. The introduction of the Bitonic edge detector marks a significant advancement in the field of medical image analysis, offering a promising solution to a longstanding challenge. Its success serves as a testament to the potential of innovative algorithms in overcoming complex problems in medical imaging and underscores the importance of continued research and development in this critical area. The clinical implications of this work are profound, as accurate edge detection in magnetic resonance (MR) images is essential for various aspects of medical practice, including disease diagnosis, surgical planning, and treatment monitoring. The introduction of noise-robust edge detectors, such as the Bitonic and Structural variation Bitonic edge detectors, has the potential to significantly enhance the quality of care delivered to patients.

Accurate edge detection is crucial for identifying anatomical structures and abnormalities in MR images, which is essential for making accurate diagnoses and developing effective treatment plans. By improving the accuracy and F-measure of edge detection in MR images, noise-robust edge detectors can help clinicians make more informed decisions, leading to more accurate diagnoses and improved treatment outcomes. Furthermore, noise-robust edge detectors can also streamline the process of surgical planning by providing clearer delineation of structures, reducing the risk of errors during procedures. Additionally, in treatment monitoring, these detectors can help track changes in anatomical structures over time, allowing for more effective evaluation of treatment efficacy. Overall, the introduction of noise-robust edge detectors in MR image analysis has the potential to significantly improve patient care by enabling more accurate diagnoses, enhancing surgical planning, and improving treatment monitoring.

In summary, this thesis represents a significant advancement in the field of edge detection in MR image datasets affected by escalating levels of noise. Our research not only addresses the immediate challenge of noise but also heralds the emergence of noise-robust solutions in medical imaging, promising transformative implications for healthcare. Looking ahead, our vision is to cultivate a healthcare ecosystem where the analysis of MR images transcends mere precision to become a driving force in elevating the standards of care. By enhancing the accuracy and F-measure of edge detection in MR images, we aim to improve patient outcomes, facilitate more accurate diagnoses, and push the boundaries of medical science. Our work underscores the importance of continued research and innovation in medical imaging, paving the way for a future where healthcare is more precise, personalized, and effective.

6.2 Future Scope

Edge detection in MR image datasets is a critical task in medical image analysis. This task becomes especially challenging when images are affected by increasing levels of noise. Here, we explore the future scope and potential research directions for noise robust edge detection algorithms in MR imaging.

- **Adaptive Noise Robust Algorithms**: Develop edge detection algorithms that adapt to varying noise profiles and levels, utilizing machine learning and statistical modeling to autonomously adjust parameters.

- **Deep Learning Advancements**: Explore advanced deep learning architectures, such as recurrent neural networks (RNNs) and attention mechanisms, for noise-resilient edge detection. Investigate transfer learning and domain adaptation techniques.

- **Real-Time Edge Detection**: Optimize edge detection algorithms for real-time or near real-time processing on modern hardware. Consider hardware acceleration (e.g., GPUs or TPUs) for efficiency.

- **Multi-Modal Integration**: Investigate approaches to seamlessly integrate data from multiple imaging modalities (e.g., MR, CT, PET) to improve edge detection accuracy.

- **Clinical Validation**: Collaborate with healthcare institutions to conduct extensive clinical validation of noise robust edge detection algorithms in real-world clinical scenarios.

- **User-Friendly Software Tools**: Develop user-friendly software tools with intuitive interfaces, visualization features, and automation capabilities to assist clinicians and researchers.

- **Benchmarking Challenges and Datasets**: Create standardized benchmark datasets and organize challenges focused on noise robust edge detection. Encourage open-source solutions.

- **Explainability and Interpretability**: Address the need for explainability and interpretability, particularly in a medical context, when integrating deep learning techniques.

- **Resource-Constrained Environments**: Optimize edge detection algorithms for deployment on low-power devices, facilitating edge detection at the point of care.

- **Ethical and Privacy Considerations**: Develop algorithms that adhere to privacy regulations while maintaining high performance in handling sensitive medical data.

The future scope in the field of edge detection for MR image datasets in the presence of increasing noise levels is vast and promising. Advancements in adaptive algorithms, deep learning, real-time applications, clinical validation, and user-friendly tools will be pivotal in addressing the challenges posed by noise in MR imaging. Collaboration between researchers, healthcare professionals, and technology providers will be instrumental in driving these advancements and ultimately improving patient care in the field of medical imaging.

List of Publications

- Parmar, G. D. and Shah, T. V. “Traditional and state-of-the-art edge detectors” Stochastic Modeling & Applications Journal Vol. 25 No. 3 Page. 2048-2054, 2021.
- Parmar, G. D. and Shah, T. V. “Effectiveness Analysis of Holistically-Nested Edge Detector for Brain Tissue Segmentation in Single-Channel MR Image” Stochastic Modeling & Applications Journal Vol. 26 No. 3 Page. 441-449, 2022.
- Parmar, G. D. and Shah, T. V. “Effectiveness Analysis of Richer Convolutional Features Edge Detector for Brain Tissue Segmentation in Single Channel MR Image” NeuroQuantology Journal Volume 21, Issue 1 Page150-157, 2023.

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