Development of Image Quality Enhancement System for Healthcare Applications

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DEVELOPMENT OF IMAGE QUALITY ENHANCEMENT SYSTEM FOR HEALTHCARE APPLICATIONS

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Abstract— To address the presence of noise in the images, the bilateral filter (BF) as a preprocessing step is used in this project. Subsequently, we employed Convolutional Neural Network (CNN) techniques for segmentation to accurately identify the tumor region and enhance an image. Training, testing, and validation of dataset MRI images were used. Based on the technique the images detect tumors or not. The results of the work were evaluated using various performance metrics such as accuracy and SNR. In the proposed methodology image enhancement using Resnet 50 exhibits the superior performance of SNR of 60db and accuracy of 98% by employing image segmentation for the detection of tumor compared to existing approaches.
Keywords— Computed Tomography, Contrast enhancement, Image processing, Retinex, CNN (Resnet 50), Image segmentation, Brain tumor.

I. INTRODUCTION

An important role is played by Medical imaging in current medical research and clinical practice. The development and application of image enhancement techniques lie in the need to overcome limitations and challenges associated with raw images. These techniques aim to improve visual perception, enhance information extraction, compensate for imaging deficiencies, enhance image aesthetics, enable more accurate analysis and interpretation, and facilitate comparative analysis. By addressing issues such as noise, blurring, low contrast, and other imaging limitations, image enhancement techniques play a vital role in enhancing image quality, enabling precise interpretation, and extracting significant information. These techniques find wide-ranging applications in fields such as healthcare, surveillance, visual media, and computer vision, where clear and detailed images are critical for decision-making, diagnosis, and analysis. Applications of Image Enhancement are sharpening, image restoration, video editing, and image recognition.

II. IMAGE QUALITY ENHANCEMENT IN HEALTH CARE APPLICATIONS

Image Quality Enhancement for healthcare applications revolves around addressing the limitations and challenges associated with raw medical images. In the healthcare field, accurate diagnosis and treatment planning heavily rely on high-quality images. However, medical images often suffer from issues such as noise, artifacts, low contrast, and blurriness, which can hinder the interpretation by healthcare professionals. The goal is to develop tailored image enhancement techniques specifically for healthcare, aiming to improve image quality. The objective is to enhance sharpness, clarity, contrast, and overall visual appearance while preserving crucial diagnostic information. the development of image quality enhancement techniques for healthcare applications aims to enhance diagnostic accuracy, improve treatment planning, and ultimately contribute to better patient outcomes in the medical domain. This can be done using various deep-learning techniques. One of them is CNN, which helps to improve images.

III. LITERATURE SURVEY

In our review of the literature, we provide a summary of different processing methods that have been introduced for segmentation and for image enhancement. The summaries of each paper are provided below, outlining their main contributions and methodologies.

Ultrasound image quality enhancement plays a vital role in improving the diagnostic value of ultrasound images, which often suffer from limitations and artifacts. the progress made in [1], enhancing ultrasound images, ranging from traditional filtering methods to machine learning-based approaches. The development of standardized evaluation frameworks is essential to ensure reliable and effective ultrasound image quality enhancement for clinical applications. However, there are certain drawbacks to consider. These include small and potentially non-representative sample size, a lack of thorough comparisons with existing methods, and no mention of clinical validation.

L.Kang et.al has introduced a novel approach that utilizes convolutional neural networks (CNNs) to evaluate image quality without requiring a reference image. By leveraging deep learning techniques, the authors demonstrate that CNNs can autonomously learn quality features from images and accurately predict their perceived quality. This significantly advances the field of image quality assessment by offering a methodology that eliminates the need for reference images, thereby increasing its practical applicability in real-world scenarios where reference images may be unavailable [2].

S.bosse et.al, presented a novel approach to enhance image quality using a deep neural network. The network is trained end-to-end and consists of ten convolutional layers and five pooling layers for feature extraction, making it deeper than existing models. One key feature of their architecture is their versatility to be used in both no-reference and full-reference image quality enhancement scenarios. Unlike traditional methods, their approach is purely data-driven and does not rely on handcrafted features or prior knowledge of the human visual system or image statistics [3].

F. Russo described a method that merges sharpening and noise reduction techniques to enhance images. The objective of the technique was to enhance image quality by simultaneously improving the clarity of details and reducing unwanted noise. The paper likely included experimental results and analysis to demonstrate the efficacy and advantages of the proposed image enhancement approach. [4]

C. Hemasundara Rao Prasad et.al , presents a method for accurately detecting and segmenting brain tumors using conditional random fields (CRF). They proposed a technique that leverages the probabilistic graphical model of CRF to incorporate spatial dependencies and contextual information in the segmentation process. By considering the relationships between neighboring pixels and utilizing relevant features, the proposed approach aims to enhance the precision and reliability of brain tumor detection and segmentation [5].

IV. CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (CNN) is a specialized type of artificial neural network that excels at processing and analyzing visual data like images and videos. Inspired by the human visual system, CNNs are widely used in computer vision tasks such as image classification, object detection, and image segmentation.

Pooling layers, such as max pooling or average pooling, are also employed to reduce spatial dimensions while retaining important features, making the network more robust to variations. The final layers of a CNN typically consist of fully connected layers that combine the learned features and produce predictions.

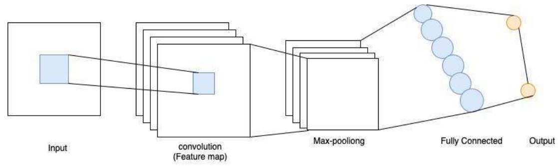

Fig-1:Architecture Of Cnn

V. CNN For IQE

CNN deep for IQE The shallow neural network might not be able to accurately imitate the perception of HVS in evaluating the image due to the complexity of the content of medical ultrasound images. For this reason, the deep convolutional neural network used in this study is used to evaluate the quality of medical ultrasound images. Humans are sensitive to the distortion between pictures, according to a study on HVS. As a result, we first teach CNN to distinguish between distorted images and their associated undistorted ones. After that, each image is objectively scored based on an estimated amount of distortion. It makes an effort to mimic human perception. In light of this, this study builds a deep CNN to perform IQE, known as DCNN-IQE-14. This network expands DCNN-IQE-8 by six convolutional layers, and the first step of analysis predicts the structure of the objective error map. Since just the convolution layer is present, the entire network is a full convolution network. Each convolution layer uses a zero padding method to keep the pixel information intact, and two down-sampling procedures are utilized to shrink the data dimension. With the exception of the final layer, every layer has a 3x3 convolution kernel that is activated by ReLU. The error map prediction is output by the 11 convolution kernel in the final layer. If quality assessment is done in the second step without first using the error map.

VI. Abbreviations

IQE: Image Quality Enhancement
CNN: Convolutional Neural Network
MRI: Magnetic Resonance imaging
RNN: Residual Neural Network

VII. Proposed Methodology

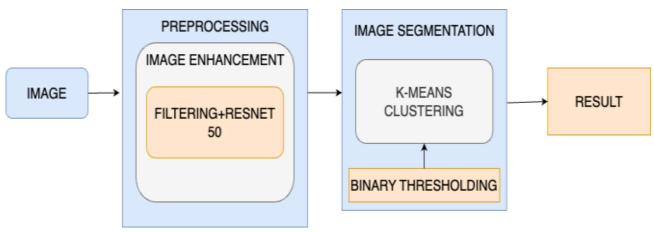

Fig-2 :Datasets Of MRI Images

The above block diagram Figure: describes the implementation of this project from the initial to the final stage

A. *Input Image*

The dataset comprises a total of 253 brain MRI images, which are categorized into two groups: 155 brain images with tumors and 98 brain images without tumors. The

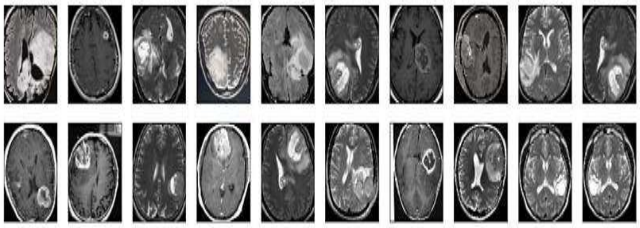

Fig-3:Datasets Of MRI Images

images from the dataset are displayed below. The magnetic resonance image (MR image) is the input for this paper. It creates images of the organs using radio waves and powerful magnetic fields

B. *Data set of MRI images*

CNN is used to automatically detect brain tumors. In order to discriminate between tissues that contain tumors and that do not, this study employs input photos from the raw data that are labelled (yes or no) as input images. 2065 sample photos, 1085 of which had tumors and 980 of which did not, were used to train CNN. As a result, the suggested system is the method suggested in this research.

The first step involves wrapping and cropping the input image. During wrapping, the input image is compared to the central object's edge in the image. The maximum edge of the image is calculated based on this comparison, ensuring that the object in the image is preserved when cropping is performed. Since the images within the dataset have different sizes, it is necessary to resize them after the cropping process. The resizing is performed to ensure that all images have a consistent shape (image width, image height, and number of channels). By resizing images to this standardized shape, it allows for easier processing and analysis during subsequent stages of the workflow. To aid in the learning process, use normalization to scale pixel values to the range from 0 to 1. Brain tumors are frequently found and diagnosed using medical imaging techniques like Magnetic Resonance Imaging (MRI) However, because of the multiple factors that can alter the quality of MRI pictures, including patient movements, technical constraints, and image artifacts, it can be challenging to precisely detect and diagnose brain tumor picture caliber The accuracy of detecting brain tumors can be impacted by low-quality MRI scans, which can be identified using enhancement techniques. The quality of MRI pictures is often evaluated using quantitative methods, such as image intensity, texture, or analysis of image attributes

Deep learning-based techniques, particularly CNNs, have recently demonstrated promising outcomes in medical image analysis, including the diagnosis of brain tumors. These techniques can be used to extract characteristics from MRI pictures and categorize them as either normal or abnormal, depending on whether or not brain tumors are present. Consequently, combining image quality enhancement methods with CNN-based approaches may increase the precision of brain tumor identification. Medical personnel can acquire or reprocess pictures to increase their quality by identifying low-quality MRI scans, which can result in more precise diagnoses and better patient outcomes.

Preprocessing

Pre-processing is applied to the photos that are gathered. Basic procedures in pre-processing include picture scaling and adding Gaussian filters for a great, clear input image for simple image recognition.

C. *Image Enhancement Using CNN*

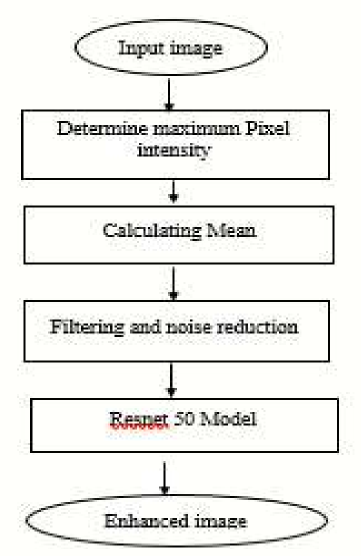

Fig-4:Flow Chart Of Image Enhancement USING Resnet50

a. Pixel Intensity

Enhancement starts with pixel intensity.To determine the pixel intensity of the image in matlab, we can load the image using the **imread** function.

image = imread('path/to/image.jpg');

b. Mean

To determine the mean intensity of an image in MATLAB, you can follow these steps: Begin by loading the image using the **imread** function and assigning it to a variable. If the image is in color and you intend to compute the mean intensity across all channels, convert it to grayscale using **rgb2gray**. Next, employ the **mean** function on the grayscale image to calculate the mean intensity. This outcome represents the mean intensity of the image, which can be stored in a variable for any subsequent analysis or processing needs.

c. Filtering Process

Filtering and noise reduction are essential in image processing to enhance image quality by eliminating unwanted noise. The general process involves pre-processing the image, analyzing the noise characteristics, selecting an appropriate filter, applying the filter, performing post-processing, and evaluating the results. Pre-processing ensures the image is suitable for filtering, while noise analysis helps in choosing the right filter. Various filters like Gaussian, median, or Wiener are used to reduce specific noise types.

d. Resnet-50

During the data preparation stage, data augmentation is employed to expand the dataset and prevent overfitting, especially when dealing with limited data. This technique involves applying various transformations such as image rotation, shear, width shift, height shift, and zoom, which effectively increase the dataset size and introduce diversity. By augmenting the data, more generalized and robust models can be developed while mitigating the risk of overfitting.

To extract meaningful features from CT scan images, a pre-trained model like ResNet-50 is utilized as a standalone tool. This model has been trained on a dataset like ImageNet and is capable of extracting distinctive feature representations from images. By feeding an image into the ResNet-50 model, it produces a numerical vector that encapsulates the significant features of the image. These extracted features can then be used as inputs for subsequent classification or analysis tasks, leveraging the knowledge captured by the pre-trained model.

f. Enhanced Image

The final output of the enhanced image using Resnet 50 is an image with a smoother and cleaner appearance.

Histogram Equalization:

To enhance the contrast of images, the histogram-based technique called equalization is commonly used. This technique involves expanding the range of intensities in the image and redistributing the most frequent intensity levels.

Sharpening :

As the name implies, sharpening is used to sharpen and accentuate the edges and emphasize how features and details move from one to the next. Sharpening, however, doesn't consider whether it is emphasizing the image's intrinsic features or the noise surrounding them. It improves both.

D. *Image Segmentation*

Segmentation

Pre-processed photos will be divided digitally into different pixels at this level of deployment. To improve a picture's representation and provide greater clarity for research and analysis, we segment the image and to detect the tumor.

Data Augmentation: Due to the insufficiency of data in the dataset for training a Convolutional Neural Network (CNN), the augmentation method is employed to address the problem of data imbalance. Augmentation is an approach that utilizes statistical data to construct a comprehensive model. It generates multiple two-dimensional images with varying poses and dimensions. By applying augmentation, the CNN segmentation accuracy can be improved by incorporating diverse variations of the images. Specifically, an image with or without a tumor is divided into individual images, each representing an image with a tumor. After data augmentation, the dataset consists of both tumor and non-tumor samples, resulting in a total of 1,050 images. These images exhibit variations in intensity, contrast, and size, which are pre-processed to facilitate smoother training.

Binary –Thresholding

Binary thresholding is an image processing technique that transforms an image into a binary format by assigning a binary value to each pixel based on a specified threshold. Pixels with intensity values below the threshold are assigned one binary value (e.g., 0), while those equal to or above the threshold are assigned another binary value (e.g., 1). This process produces a binary image where objects of interest are represented by one binary value against a contrasting background. Binary thresholding is frequently employed to simplify images, emphasize particular regions, or facilitate object separation for subsequent analysis.

K-Means Clustering

K-means clustering is an unsupervised machine-learning technique used to group similar data points together. It works by dividing a dataset into k clusters, where each data point is assigned to the cluster with the closest average value. The algorithm starts by randomly selecting k initial cluster centroids. It then iteratively assigns data points to clusters based on their proximity to the centroids and updates the centroids by computing the mean of the assigned data points. This process continues until convergence, where the cluster assignments no longer change significantly. The objective is to minimize the squared distances between data points and their respective centroids.

How k-Clustering Works:

A certain value is set for this purpose so that if it is lower than the matching value, the part is unaffected, and if it is higher or equal to the matching value, the part is

affected by the tumor. Then, in order to discriminate between the tumor and the unaffected area of the brain, we must obtain clusters affected by the tumor. Then, in order to discriminate between the tumor and the unaffected area of the brain, we must obtain clusters. figure-4.6 shown below is the original and preprocessed sample input after the clustering method

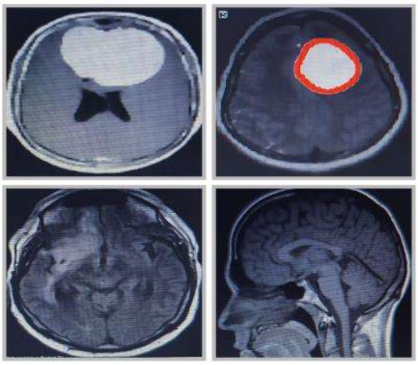

Fig-5:Example of a figure with Tumor and Non-Tumor images

VIII. PERFORMANCE ANALYSIS

Performance analysis of image enhancement and segmentation involves assessing the effectiveness and accuracy of these techniques in improving image quality and identifying specific objects or regions. During the experimentation phase, it was

noted that the suggested methodology consistently outperformed alternative approaches across various image sets. However, when examining different methods, it became evident that the proposed Convolutional Neural Network (CNN) method exhibited superior output quality specifically MRI images using RESNET-50. This observation is supported by the data presented in tables In summary, the CNN-based approach demonstrated significantly improved results for images of a specific method compared to the existing method.

Methods	ACCURACY(%)	SNR(dB)
Weiner filter	32	11
TBCSSR	**63**	**21**
RESNET50 (proposed)	**97**	**60**

TABLE:Comparison of Results of Proposed and Existing Methodology

Fig-6:Raw Image

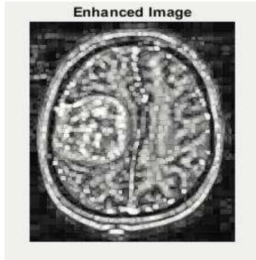

Fig-7:Enhanced image

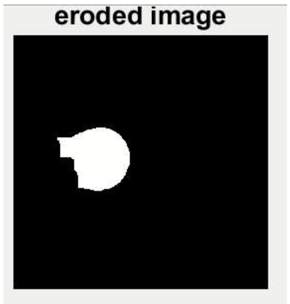

Fig-8:Eroded Image

Fig-9:Image Of Tumor Detected

Fig-10:Image Of Non-Tumor

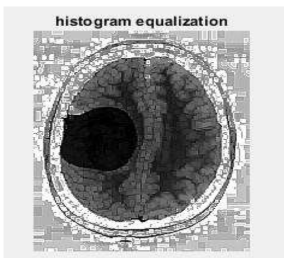

Fig-11:Histogram Equilisation

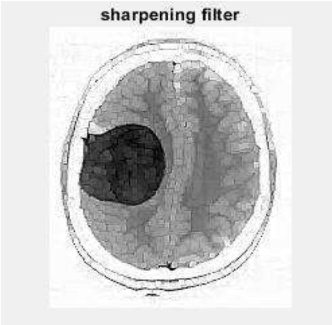

Fig-12:Sharpening Filter

IX. Conclusion

It is a technique that can be used to spot and classify a brain tumor by segmenting MRI pictures of the brain. With the highest accuracy, this technique calculates the tumor's size. In this study, we used image processing to automate the process of identifying a brain tumor. Our project has demonstrated to provide an overall accuracy of various types of filters and turbo-tuned technique Convolutional Neural Networks, in addition to several existing methodologies for segmentation and detection of brain tumors for MRI images of the brain, and will improve the image quality by segmenting the affected area. Enhancement and filtration are crucial because they have sharpened edges, and remove noise.

X. Future Scope

During the decimation process, it has been observed that the proposed approach requires a large training set to achieve more accurate results. However, in the field of medical image processing, obtaining a sufficient amount of medical data is a challenging and time-consuming task. In many cases, datasets may not be readily available. In such scenarios, it is crucial for the proposed algorithm to exhibit robustness in accurately identifying abnormal regions from MR images. To address this limitation, the proposed approach can be further improved by integrating weakly trained algorithms. These algorithms have the capability to identify abnormalities even with minimal training data. Additionally, incorporating transfer learning algorithms can contribute to enhancing the accuracy of the algorithm while reducing computational time.

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