COMPARISION OF PREPROCESS TECHNIQUES FOR BRAIN IMAGE USING MACHINE LEARNING

S.Jayasudha1, K.Pershi2, M.Mahamayee3, K.RajKumar4, Mrs.G.R.Hemalakshmi5
[1,2,3]*UG Students, Computer Science and Engineering Department, National Engineering College*
[4,5]*Ass. Prof., Computer Science and Engineering Department, National Engineering College*

Abstract: A brain tumour is the second leading cause of death in young people.. Tumors of the brain come in a wide range of shapes and sizes. Noncancerous brain tumour exist alongside cancerous brain tumors. In medical image processing, detecting and segmenting brain tumors is extremely difficult. Four forms of preprocessing are used here: Adaptive Median Filter (AMF), Median Filter, Gaussian Filter and Wiener Filter. The performance metrics were then determined using the following

1.The Mean Square Error Rate (MSE) is a measurement of a system's accuracy.

2.Signal-to-Noise Ratio at Peak (PSNR)

3. Structure Similarity Index

4.Number four is the Spearman rank correlation. The Adaptive median Filter produces the best results for both regular and abnormal images based on the above measurements.

***Keywords*: A brain tumor, Filter, and Measurement of Efficiency**

1. Introduction

A brain tumour is described as an irregular growth and abnormality of extracellular material in the brain. Tumors develop as a result of uncontrolled cell growth. It is possible to classify a tumour as primary or secondary based on its origin (metastatic). The aggressiveness of a brain tumour is difficult to assess.

Cancer cells that have spread across the brain begin to expand in every part of the body.

Breast or lung cancer cells, for example, often travel via the bloodstream to the brain. Brain tumors that have spread to other parts of the body are often cancerous. The benign tumour grows slowly and isn't as dangerous as the malignant tumour. It rarely spreads and has well-defined boundaries.

Surgery is the most effective treatment for this issue, though it is less dangerous. The growth rate of malignant tumors is uncontrollable and rapid. This is a life-threatening situation that necessitates immediate medical attention.The tumour is diagnosed based on the morphology of the tumour cells, as well as certain tumour cell characteristics such as rate of development, appearance, dead tumour cells in the tumor's middle, blood supply, and invasive potential. Tumors are classified into four categories by the World Health Organization (WHO) based on their rate of development, blood supply, dead cells, uncontrolled growth, and healthy cells.

2. MethodologiesUsed

2.1 Adaptive MedianFilter(AMF):

The Adaptive Median Filter is used for method comparisons that are more sophisticated than traditional median filtering. It uses spatial processing to determine which pixels in an image are impacted by impulse noise. It decides whether pixels in an image are noise by comparing each pixel to its neighbour pixels.The size of the neighbourhood and the reference threshold can also be changed. Noise is described as a pixel that deviates from the majority of its neighbour and is not aligned with those pixels to which it is identical. The median pixel value in the neighbourhood that passed the noise labeling test is then used to replace the impulse noise pixels.The purpose of adaptive median filter(AMF) is:

1)Remove impulsenoise.

2)Smoothing of othernoise.

3)Reducedistortion.

2.2 Medianfilter:

In the same way that the mean filter reduces image noise, the median filter does as well.However, it surpasses the mean filter in terms of retaining useful image detail. This type of filter belongs to the non-linear edge-preserving smoothing filter family.This indicates that in this two images A(x) and B(x)

$$median[A(x)+B(x)] \neq median[A(x)]+median[B(x)]$$

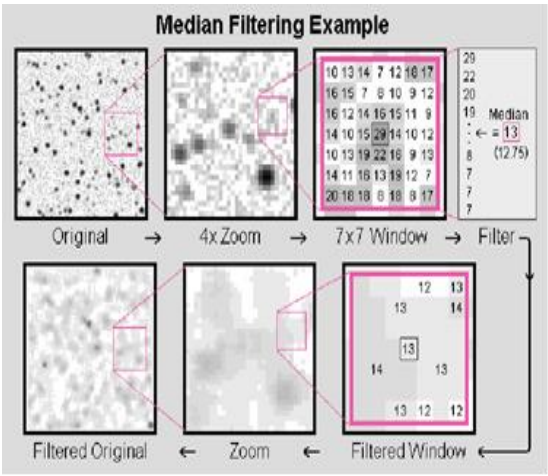

Fig1: illustration example of median filtering.

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These filters smooth data while keeping images fine and clear. Aggregate of all the pixels's value in the neighborhood is the median value.The median outperforms the average as a "key predictor." A small number of outlier pixels in the neighborhood, in particular, have little impact on the median. Median filtering is extremely effective at removing different forms of noise.

2.3 GaussianFilter:

To blur images and eliminate noise and information, Gaussian filters are applied. Its properties include no overshoot to a phase function input and minimal rise and fall times. The Gaussian filter has the smallest possible group delay, which explains this action. It is widely considered to be the best time-domain filter currently available. The Gaussian function is used in a wide range of areas, including mathematics and statistics.

- ✓ It establishes a probability distribution for data or noise.
- ✓ It's a smoothing function.
- ✓ It is used inmathematics.

2.4 WeinerFilter:

The Wiener filter is a linear time-invariant (LTI) filter that is used to approximate a desired or target random process from an observed noisy

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)},$$

process. Between the calculated random process and the ideal process, it minimises the mean square error. It achieves the best possible balance between inverse filtering and noise smoothing.

It aids in the removal of additive noise while also inverting blurring. A linear estimation of the original image is used in Wiener filtering. This method employs a stochastic system. According to the orthogonality theorem, the Wiener filter in the Fourier domain can be written as follows:

where $S_{xx}(f_1, f_2)$, $S_{\eta\eta}(f_1, f_2)$ are the original image's power spectra and

additive noise's power spectra, and where is the blurring filter? $H(f_1, f_2)$ It is divided into two sections: an inverse filtering section and a noise smoothing section. It not only uses inverse filtering to perform deconvolution, but it also uses compression to eliminate noise.

2.5 Mean SquareError(MSE)

MSE is determined by multiplying the actual output minus expected output by the square of the prediction error, then dividing by the number of data points. It provides an absolute number indicating how far the expected results differ from the actual number. It's a probability function that corresponds to the squared error loss's expected value. The MSE is a non-negative metric that measures an estimator's efficiency. The closest it is to zero, the better.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

2.6 Peak signal-to-noise ratio (PSNR)

It's an expression for the representation efficiency that affects the ratio of a signal's maximum potential value to the power of distorting noise. The PSNR is represented in logarithmic decibels since many signals have a broad dynamic range. Picture enhancement is a subjective method for improving a digital image's visual quality. Quantitative/empirical comparisons must be developed to compare the impact of contrast enhancement technologies on picture quality. Different image enhancement algorithms can be compared consistently using the same collection of test images to see which algorithm produces better performance. If an algorithm or group of algorithms can improve a degraded known image so that it looks more like the original, we can infer that it is a better algorithm.

2.7 Structural Similarity IndexMeasure(SSIM)

The structural similarity index is a metric that can be used to predict the perceived consistency of digital television and cinematic images, as well as other digital images and videos. It's used to compare two pictures to see how close they are. The SSIM index is an all-encompassing benchmark metric. The SSIM model is a perception-based model that recognises image deterioration as a change in perceived structural details. Some techniques, such as MSE or PSNR, estimate absolute errors, while these methods estimate relative errors. Structural knowledge refers to the concept that pixels have a lot of interdependencies, particularly when they're close together in space.

2.8 Spearman's Rank CorrelationCoefficient

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

The Spearman's Rank Correlation Coefficient aids in determining how strong a similarity between two sets of data is. The Pearson correlation between some of the grade values of two variables is very much like the Spearman coefficient of correlation. When there is no rank, the Spearman rank correlation formula is:

The following data assumptions must hold for the estimation of Spearman's correlation coefficient and subsequent signify to test: interval or ratio level and monotonically connected.

3. Results andDiscussion:

The images in the following table show how various preprocessing techniques, such as Adaptive Median Filter, Median Filter, Wiener Filter, and Gaussian Filtering, were used to create regular and abnormal images.

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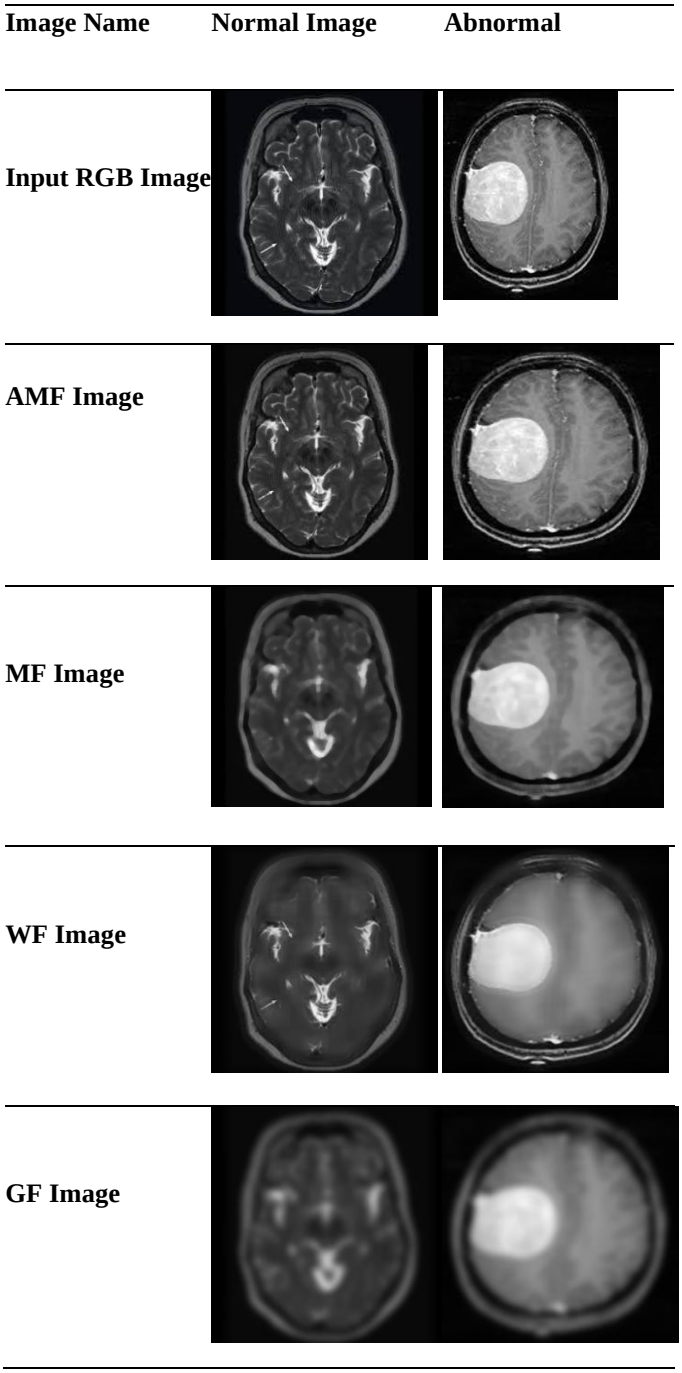

Fig 2: Images after applying Different Filtering Techniques(Normal and Abnormal)

3.1 Performance analysis of Adaptive Median Filter:

In this portion, the adaptive median filter (AMF) is compared to other preprocessing filters such as the MF, WF, and GF in terms of performance metrics such as MSE, SSI, SRC, and PSNR. The analysis of regular and abnormal brain images is given in the following two tables.

Table 2: AMF Comparison with Median, Wiener, and Gaussian Filters for Normal Brain Image Images

Measure	**AMF**	Median	Wiener	Gaussian
MSE	**22.77735**	428.2447	245.2923	165.8143
PSNR	**36.39467**	22.39588	25.56695	26.57122
SSI	**0.979463**	0.645254	0.807289	0.743849
SRC	**0.988569**	0.90729	0.948931	0.938669

Table 3: AMF Comparison with Median, Wiener, and Gaussian Filters for Abnormal Brain Images

Measure	**AMF**	Gaussian	Median	Wiener
MSE	**23.18177**	493.6287	280.7604	188.8412
PSNR	**35.01962**	21.36263	24.04457	25.67844
SSI	**0.979392**	0.625747	0.79981	0.716862
SRC	**0.990601**	0.917842	0.950311	0.948494

4. Conclusion:

This article uses machine learning to compare four types of pre-processing techniques for brain images (Adaptive Median Filter(AMF), Median Filter, Gaussian Filter, and Wiener Filter). As compared to all other methods, the Adaptive median Filter produces the best results for both normal and abnormal videos, according to the results of the above investigation.

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