International Journal of Computer Science
Oddity...Probe...Reviste...
http://www.ijcsjournal.com Volume 1, Issue 2, No 5, 2013. ISSN: 2348-6600
Reference ID: IJCS-SI-24 PAGE NO: 001-016

TUMOR DETECTION IN MRI AND MAMMOGRAM IMAGES USING STATISTICAL TEXTURE ANALYSIS AND FEATURE EXTRACTION

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Abstract - Tumour images obtained are used for further diagnosis and prediction pertaining to type of tumor. Medical images are used to diagnosis the possibility of diagnosis. However, there is a higher possibility of false detection of the images as the manual and personal knowledge of the expert is involved in this. Digital Images obtained are analyzed based on the statistical features and characteristics. Digitized images for further diagnosis in case of suspected Brain tumor. MRI technique is used to obtain these 2D images of Brain map. In case of Breast tumor diagnosis, the technique used is Mammography. These images are in digital form and in two dimensional in nature. Image analysis and their statistical feature abstraction is one of the important aspects in process to early detection of tumor existence, their size and type of tumor. This can be helpful in early detection and rapid follow up actions to cure the problem. This study aims to work on aspects of digital image analysis using its statistical features and how they can be used for the purpose of early detection. Datasets of images are obtained for both Brain tumor images using MRI and Breast tumor images using Mammogram. These images are in digital forms and contain noise. Using appropriate noise removal technique, the obtained datasets are used for statistical analysis using SciLab®. The feature extraction technique is used to obtain the area of interest. Statistical measurement matrices are generated for the purpose of area of interest identification. The measured features are used to verify and observe the results using blind datasets. Tumor texture and statistical analysis can be done using this to identify the similarities and difference among the obtained results of both types of tumors. The obtained results show that above 67% of blind dataset images of brain tumor and above 84% of breast tumors falls within the obtained statistical measurement matrices.

Keywords: : Brain and breast tumour, Digital Image Statistical features, Image texture analysis, Digital Image analysis, Medical Image Analysis.

1. Introduction

Medical imaging plays an essential role in the diagnosis and analysis of abnormal tissue structures within the human body. Images obtained through medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, and Mammography

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are widely used by medical practitioners to assist in the detection and evaluation of tumors. These images provide visual information regarding the presence or absence of abnormal tissue growth and help in identifying the location and approximate size of the suspected tumor region. However, in many cases it is difficult to accurately determine the nature, growth tendency, and severity of the tumor based solely on visual inspection. It is frequently observed that a suspected tumor region may eventually be identified as benign in nature.

Medical images obtained through radiographic and imaging devices are generally represented in digital form and consist of two–dimensional pixel-based structures. During the image acquisition process, various types of noise and artifacts may be introduced due to limitations of imaging devices, environmental factors, or scanning procedures. The presence of such noise may degrade the quality of the original image and affect the accuracy of further analysis. Therefore, preprocessing of medical images becomes a necessary step before applying image analysis techniques.

Image preprocessing primarily involves noise removal and image enhancement techniques that improve the overall quality of the image. Background noise and unwanted artifacts present in medical images can lead to distortions and irregularities that influence the interpretation of the image. Hence, removal of noise and enhancement of image quality are important preparatory steps in medical image analysis. The objective of preprocessing is to obtain refined images that are suitable for further processing, feature extraction, and algorithmic analysis.

In many cases, medical images may also contain additional elements such as labels, annotations, borders, or markers introduced during the imaging process. These superimposed components may appear as high or low intensity regions that are not related to the actual anatomical structures. Such elements must be appropriately removed or filtered during the preprocessing stage in order to obtain accurate representations of the original image.

Various filtering techniques are commonly applied for the purpose of noise removal and image enhancement. Filters are generally used to eliminate unwanted artifacts and improve the quality of the image within the spatial domain. The commonly applied filtering techniques in digital image processing can broadly be categorized into the following groups:

1 Image smoothing
2. Image sharpening
3. Noise removal
4. Edge detection

In digital image processing, a filter is often implemented in the form of a kernel, which is a small matrix applied to each pixel of the image. The kernel operates on individual pixels along with their neighbouring pixels to compute a modified pixel value. This process is repeated across the entire image to generate a refined output image with improved characteristics.

The quality of the processed image can be evaluated using standard performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). These parameters provide quantitative measures to determine the effectiveness of noise removal techniques and the degree of similarity between the processed image and the original image.

Several filtering techniques are commonly used in the preprocessing stage of medical image analysis. Some of the widely applied filters include the following:

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Median Filter:

The median filter is a nonlinear filtering technique that is highly effective in removing impulsive noise such as salt-and-pepper noise. This filter replaces the value of a pixel with the median value of the neighbouring pixel intensities. An important advantage of the median filter is that it preserves the edges of the image while removing noise. Variants of median filtering include centre-weighted median filters, weighted median filters, and max-median filters.

Mean Filter:

The mean filter replaces each pixel value with the average value of the intensity levels within its local neighbourhood. This method helps in reducing local variations in intensity and provides a smoothing effect. Although it is simple and easy to implement, the mean filter often leads to blurring of image edges. It performs optimally in cases where the noise follows a Gaussian distribution; however, it may not be effective for multiplicative noise such as speckle noise.

Adaptive Mean Filter:

To overcome the limitations of the conventional mean filter, adaptive mean filtering techniques have been proposed. These filters adjust their behavior based on the local statistical properties of the image. By adapting to the variations in image regions, the adaptive mean filter is capable of reducing speckle noise while preserving important structural features and edges. Statistical parameters such as mean, variance, and spatial correlation are used to identify and preserve important image characteristics.

Histogram Equalization:

Histogram equalization is a commonly used technique for improving image contrast. It operates by redistributing the grey level values of the image to obtain a more uniform histogram. In this process, each pixel value is modified based on the cumulative distribution function of the histogram, resulting in improved contrast and better visibility of important image features.

Among these techniques, adaptive filtering approaches are often found to provide improved performance in terms of noise reduction while maintaining important image structures. Based on experimental observations and performance evaluation using PSNR values, adaptive mean filtering techniques are considered effective for preprocessing medical images and are therefore adopted in the present study.

Image processing applied to medical images involves the transformation of image signals obtained from imaging devices into digital pixel-based representations suitable for computational analysis. These signals may originate as analog or digital signals depending on the imaging system used. The processed output may either represent the reconstructed digital image or the extracted characteristics and statistical features derived from the image.

Digital image processing has numerous applications across scientific and engineering disciplines. These applications range from the interpretation of remotely sensed images to biomedical image analysis (Acharya & Ray, 2005). In the biomedical domain, digital image processing techniques are extensively used for the analysis of medical images obtained from various parts of the human body using advanced imaging devices such as X-ray scanners, ultrasound systems, and MRI machines.

The analysis of such digital images for tumor detection and characterization has become an important area of research. Various computational algorithms and image analysis

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methods have been developed to assist medical experts in identifying abnormal tissue regions and studying their characteristics. Automated and semi-automated image analysis techniques provide an additional advantage by reducing subjectivity in interpretation and supporting early detection of tumors.

Another significant advantage of digital medical images over traditional imaging methods is the possibility of applying quantitative image analysis techniques. These methods allow objective measurement of image characteristics and reduce the dependence on purely subjective interpretation by medical experts. Quantitative analysis can therefore improve consistency in diagnosis and assist clinicians in making informed decisions.

II. Literature Review:

Medical image processing has become an important area of research for assisting medical practitioners in the diagnosis and identification of tumors. With the advancement of imaging technologies such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), ultrasound, and mammography, a large number of medical images are generated for clinical analysis. These images provide valuable information regarding the presence of abnormal tissue structures. However, manual interpretation of these images by medical experts may sometimes lead to subjective variations in diagnosis. Therefore, digital image processing techniques are increasingly used to improve the accuracy and reliability of medical image analysis.

Digital image processing techniques provide various methods for image enhancement, noise removal, segmentation, and feature extraction. These techniques play a significant role in improving the quality of medical images and facilitating the identification of abnormal regions. The application of digital image processing in biomedical imaging has been extensively discussed by several researchers (Acharya & Ray, 2005). Their work explains the importance of preprocessing, image segmentation, and feature extraction techniques for analyzing medical images and assisting medical diagnosis.

Fundamental techniques in digital image processing such as filtering, histogram processing, image enhancement, and segmentation are widely used in medical imaging applications. These techniques help in improving the quality of the acquired images and in extracting meaningful information from the image data (Gonzalez & Woods, 2008). Preprocessing techniques are particularly important because medical images often contain noise introduced during the image acquisition process.

Texture analysis has been widely used for the analysis of medical images. One of the most commonly used techniques for texture analysis is based on the Gray Level Co-occurrence Matrix (GLCM). The statistical texture features derived from GLCM, such as contrast, correlation, energy, and homogeneity, provide useful information about the spatial distribution of pixel intensities within an image (Haralick et al., 1973). These features have been widely used in the detection and classification of tumor regions.

Research studies have also explored the use of co-occurrence statistics for representing texture characteristics of images. Clausi analyzed various co-occurrence texture measures and demonstrated their effectiveness in representing structural properties of digital images (Clausi, 2002). Texture-based approaches have since been widely applied in medical image analysis for identifying abnormal tissue patterns.

Several studies have focused on automated analysis of medical images for tumor detection.

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Cheng and colleagues proposed techniques for automated detection and classification of masses in mammographic images using segmentation and feature extraction methods (Cheng et al., 2006). Their work demonstrated that automated systems can assist radiologists by identifying suspicious regions in medical images.

Medical image analysis techniques have also been extensively reviewed in the literature. Duncan and Ayache discussed the progress made in medical image analysis over several decades and highlighted the importance of image segmentation, feature extraction, and pattern recognition methods in medical diagnosis (Duncan & Ayache, 2000).

Object boundary detection is another important aspect of medical image analysis. Kass et al. introduced the concept of active contour models, commonly known as snakes, which are used to detect object boundaries in images (Kass et al., 1988). These models have been widely used in medical image segmentation for identifying tumor boundaries.

Threshold-based segmentation techniques have also been widely used for separating tumor regions from surrounding tissues. One of the most popular thresholding techniques was proposed by Otsu, which determines an optimal threshold value by minimizing intra-class variance in the image histogram (Otsu, 1979).

Wavelet-based texture analysis methods have also been explored for tumor detection. Padma and Sukanesh proposed a wavelet-based feature extraction approach for identifying abnormal tumor regions in medical images (Padma & Sukanesh, 2011). Their method used statistical texture features derived from wavelet coefficients to differentiate normal and abnormal tissues.

Feature extraction techniques based on intensity, texture, and shape features have also been used for medical image classification. Rathi and Palani proposed a method that combines feature extraction with dimensionality reduction techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for MRI image classification (Rathi & Palani, 2012).

Filtering techniques are commonly used in the preprocessing stage of medical image analysis. Filters such as median filters, mean filters, and adaptive filters are widely used for removing noise and improving image quality. These filters help in preserving important structural details while eliminating unwanted noise components.

Statistical analysis of medical images has also been used to study variations in tissue structures. Statistical measures such as mean intensity, variance, entropy, and correlation provide useful information about the characteristics of the image. These measures are often used for identifying abnormal regions and for distinguishing between normal and tumor tissues.

Several studies have also emphasized the importance of quantitative image analysis in medical diagnosis. Quantitative analysis methods help reduce subjective interpretation and provide objective measurements of image characteristics. Digital image processing techniques therefore provide valuable support to medical practitioners in identifying tumor regions and analyzing their characteristics.

Overall, the literature suggests that preprocessing, feature extraction, and texture analysis techniques play a crucial role in medical image analysis. These techniques help in improving image quality, identifying regions of interest, and extracting meaningful statistical features from medical images. However, many existing studies focus on specific imaging modalities or particular tumor types. Therefore, there is a need for more generalized approaches

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that can analyze tumor characteristics across different types of medical images.

III. Methods and Methodology:

Medical image analysis for tumor detection involves several systematic steps including image acquisition, preprocessing, feature extraction, and statistical analysis. The objective of this process is to extract meaningful information from digital medical images that can assist in identifying abnormal tissue structures. In the present study, digital image processing techniques and statistical feature analysis are applied to analyze tumor images and to identify the region of interest within the images.

Image analysis can be performed by studying the statistical and texture characteristics present in the digital images. These features represent the intensity distribution and spatial relationships among the pixels within the image. By analyzing these characteristics, it becomes possible to differentiate normal tissue regions from abnormal tumor regions. Statistical parameters such as mean intensity, variance, and spatial correlation are commonly used for describing image texture and structural properties.

In the proposed methodology, image datasets obtained from medical imaging sources are used for analysis. These datasets consist of digital images that contain tumor and non-tumor regions. Initially, a set of known images is selected for the purpose of extracting statistical features and generating measurement parameters. These known images serve as a reference dataset for analyzing the characteristics of tumor regions.

The extracted statistical features from the reference dataset are used to construct statistical measurement matrices. These matrices represent the distribution of various statistical parameters within the region of interest. The measurement matrices provide a structured representation of the feature values that correspond to the tumor regions within the images.

Once the statistical parameters are obtained from the reference dataset, unknown images are processed using the same methodology. The unknown images are subjected to preprocessing and feature extraction procedures similar to those applied to the reference dataset. The obtained statistical features are then compared with the measurement matrices generated from the reference images.

The comparison between the statistical features of unknown images and the reference measurement matrices enables the identification of similarities and variations in image characteristics. Based on this comparison, the presence of tumor regions can be identified and analyzed. The effectiveness of the methodology can be evaluated by comparing the obtained results with the actual classification of the images.

The overall methodology adopted in the present study follows a sequence of steps including image acquisition, preprocessing, feature extraction, statistical analysis, and result evaluation. The complete workflow of the proposed methodology is illustrated in Figure 1, which shows the sequential steps involved in the image processing and analysis procedure.

The flow diagram presented in Figure 1 describes the stages involved in the processing of medical images, beginning with the acquisition of digital images and ending with the evaluation of statistical analysis results. Each stage of the methodology contributes to improving the accuracy and reliability of tumor detection using digital image processing techniques.

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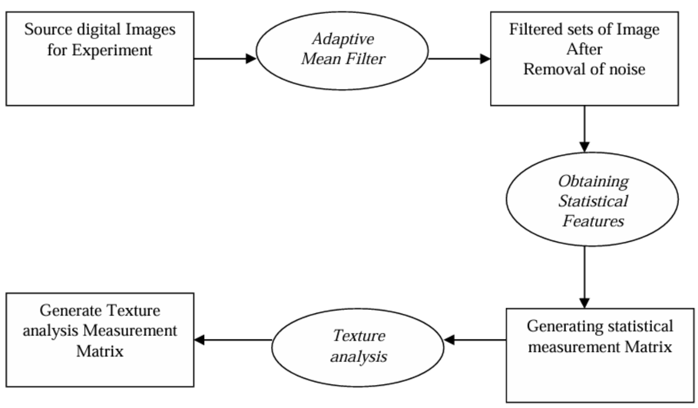

Fig.1: Process flow of Statistical and Texture analysis

For the purpose of the present study, digital medical image datasets were obtained from imaging systems that produce images with consistent resolution and acquisition parameters. The images used in the study were generated using standardized imaging equipment so as to maintain uniformity in image quality and resolution. Maintaining uniform imaging conditions is important to ensure consistency in feature extraction and statistical analysis.

Two separate datasets of tumor images were prepared for the experimental analysis. Each dataset consisted of 30 digital images, resulting in a total of 60 clinically verified tumor images. The selected images correspond to cases where the presence of tumor had been pathologically verified. These datasets therefore represent known cases and serve as the reference dataset for extracting statistical characteristics of tumor regions.

Before performing feature analysis, the acquired images were subjected to preprocessing in order to improve image quality. Medical images often contain noise introduced during the imaging process, which may affect the reliability of further analysis. In the present study, Adaptive Mean Filtering was applied as a preprocessing technique to reduce noise while preserving important image structures. The application of this filter resulted in filtered image datasets with improved clarity and reduced noise artifacts.

After the preprocessing stage, the Region of Interest (ROI) corresponding to the suspected tumor area was identified from each filtered image. Extraction of the ROI allows the analysis to focus specifically on the relevant tissue region rather than processing the entire image. This step helps in reducing computational complexity and improves the accuracy of feature extraction.

Once the ROI was extracted from the filtered image datasets, texture and statistical analysis of the pixel regions was performed. The pixel intensity distribution within the ROI was analyzed to determine the range and variability of gray-level values present in the tumor region. Based on this analysis, various statistical parameters were calculated to characterize the structural properties of the tumor region.

The statistical feature extraction process generated a set of measurement matrices representing the characteristics of the ROI. These matrices contain important statistical parameters derived from the pixel intensity distribution and texture properties of the ROI. The extracted feature set includes the following parameters:

- Minimum pixel intensity
- Maximum pixel intensity
- Mean intensity value
- Median intensity value
- Entropy
- Standard deviation
- Gray Level Co-occurrence Matrix (GLCM) based texture characteristics

These statistical feature matrices represent the structural and textural properties of tumor regions

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within the medical images. The generated matrices serve as reference parameters that can be used for further comparison and analysis of unknown image datasets.

The extracted statistical features provide quantitative information about the variation in pixel intensities and texture patterns present in the tumor regions. Such information plays an important role in identifying similarities and differences among various tumor image samples and supports the process of tumor detection using digital image analysis techniques.

IV Findings and Analysis:

The analysis of medical images in the present study was performed using statistical and texture-based feature extraction techniques applied to the Region of Interest (ROI) obtained from the filtered images. The purpose of this analysis was to quantitatively evaluate the structural and intensity variations present in tumor regions and to compare these characteristics with those obtained from blind datasets.

Image Preprocessing Evaluation

Before feature extraction, the images were processed using an Adaptive Mean Filter to remove noise while preserving important structural information. Noise removal is essential in medical image processing because noise may lead to inaccurate feature extraction and unreliable analysis results.

To evaluate the effectiveness of the filtering process, two standard image quality parameters were calculated:

- Mean Squared Error (MSE)
- Peak Signal-to-Noise Ratio (PSNR)

Mean Squared Error (MSE):

Mean Squared Error measures the average squared difference between the original image and the filtered image.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j) - K(i,j)]^2$$

Where:

- (M) and (N) represent the dimensions of the image
- (I(i,j)) represents the pixel value of the original image
- (K(i,j)) represents the pixel value of the filtered image

Lower MSE values indicate better filtering performance.

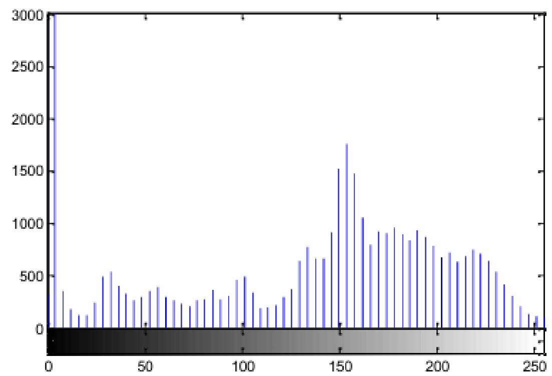

Fig.2: Histogram Representation of tumour Images

Peak Signal-to-Noise Ratio (PSNR):

PSNR is used to measure the quality of the reconstructed or filtered image relative to the original image.

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (2)$$

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Where:

- MAXI represents the maximum possible pixel value of the image (usually 255 for 8-bit images)
- MSE is the Mean Squared Error
- Higher PSNR values indicate better image quality and effective noise reduction.
- The calculated PSNR values in the filtered datasets confirmed that the adaptive filtering technique significantly improved the image quality while preserving important structural information.

Statistical Feature Analysis of ROI:

After preprocessing, the Region of Interest (ROI) corresponding to the suspected tumor region was extracted from each filtered image. The statistical analysis of the ROI was performed to study the distribution and variation of pixel intensities. The following statistical features were calculated.

Mean Intensity:

The mean intensity represents the average pixel intensity within the ROI.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (3)$$

Where:

- xi represents pixel intensity values
- N is the total number of pixels in the ROI

The mean intensity provides information about the overall brightness level of the tumour region.

A. Median Intensity:

The median is the middle value in the ordered set of pixel intensities.

$$Median = \begin{cases} x_{\frac{N+1}{2}}, & \text{if } N \text{ is odd} \\ \frac{x_{\frac{N}{2}} + x_{\frac{N}{2}+1}}{2}, & \text{if } N \text{ is even} \end{cases} \quad (4)$$

The median value is useful for representing the central intensity value when the data distribution contains outliers.

B. Standard Deviation

Standard deviation measures the spread or variability of pixel intensity values around the mean.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (5)$$

Where:

- μ is the mean intensity
- x_i are the individual pixel values
- N is the total number of pixels

Higher standard deviation values indicate greater intensity variation, which is often associated with heterogeneous tumor structures.

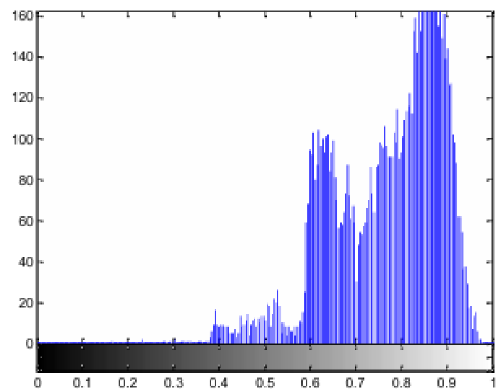

Fig.3: Histogram after applying Gaussian Filter

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1. Peak Signal-to-Noise Ratio (PSNR):

PSNR is used to measure the quality of the reconstructed or filtered image relative to the original image.

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Where:

- MAX_I represents the maximum possible pixel value of the image (usually 255 for 8-bit images)
- MSE is the Mean Squared Error

Higher PSNR values indicate better image quality and effective noise reduction. The calculated PSNR values in the filtered datasets confirmed that the adaptive filtering technique significantly improved the image quality while preserving important structural information.

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After preprocessing, the Region of Interest (ROI) corresponding to the suspected tumor region was extracted from each filtered image. The statistical analysis of the ROI was performed to study the distribution and variation of pixel intensities.

The following statistical features were calculated.

A. Mean Intensity:

The mean intensity represents the average pixel intensity within the ROI.

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i \quad (3)$$

Where:

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- N is the total number of pixels in the ROI

The mean intensity provides information about the overall brightness level of the tumor region.

B. Median Intensity:

The median is the middle value in the ordered set of pixel intensities.

$$Median = \begin{cases} x_{\frac{N+1}{2}}, & \text{if } N \text{ is odd} \\ \frac{x_{\frac{N}{2}} + x_{\frac{N}{2}+1}}{2}, & \text{if } N \text{ is even} \end{cases} \quad (4)$$

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Standard deviation measures the spread or variability of pixel intensity values around the mean.

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2} \quad (5)$$

Where:

- μ is the mean intensity
- x_i are the individual pixel values
- N is the total number of pixels

Higher standard deviation values indicate greater intensity variation, which is often associated with heterogeneous tumor structures.

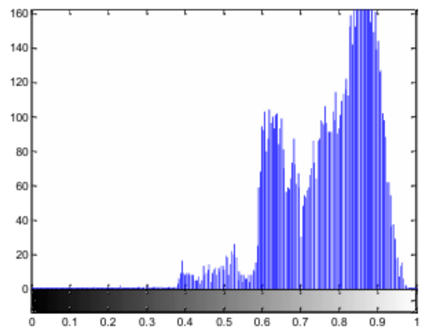

Fig.3: Histogram after applying Gaussian Filter

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D. Entropy:

Entropy measures the randomness or complexity of the image texture.

$$Entropy = -\sum_{i=0}^{L-1} p(i)\log_2 p(i) \quad (6)$$

Where:

- p(i) is the probability of occurrence of gray level i
- L is the total number of grey levels

Higher entropy values indicate more complex and irregular textures within the ROI.

TEXTURE ANALYSIS USING GRAY LEVEL CO-OCCURRENCE MATRIX (GLCM):

To further analyze the spatial distribution of pixel intensities, texture features were extracted using the Gray Level Co-Occurrence Matrix (GLCM). The GLCM represents the frequency of occurrence of pixel pairs with specific intensity values at a defined spatial relationship.

Several texture features were derived from the GLCM.

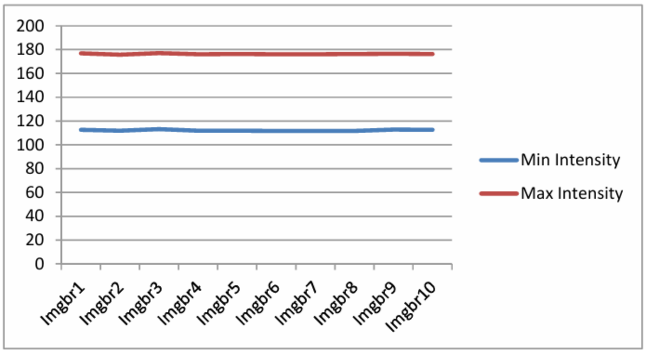

Fig.4: Min and Max Intensity boundary

E. Contrast:

Contrast measures the local intensity variation within the image.

$$Contrast = \sum_{i,j}(i-j)^2 P(i,j) \quad (7)$$

Where:

- P(i,j) represents the probability value in the GLCM.

Higher contrast values indicate greater intensity variation between neighboring pixels.

F. Correlation:

Correlation measures the degree of linear dependency between neighboring pixel values.

$$Correlation = \sum_{i,j}\frac{(i-\mu_x)(j-\mu_y)P(i,j)}{\sigma_x\sigma_y} \quad (8)$$

Where:

- μ_x, μ_y are mean values
- σ_x, σ_y are standard deviations

Correlation values close to 1 indicate strong relationships between pixel pairs.

G. Homogeneity:

Homogeneity measures the closeness of distribution of elements in the GLCM to the GLCM diagonal.

$$Homogeneity = \sum_{i,j}\frac{P(i,j)}{1+|i-j|} \quad (9)$$

Higher homogeneity values indicate more uniform textures.

COMPARATIVE ANALYSIS WITH BLIND DATASET:

After extracting the statistical and texture features from the reference dataset, measurement matrices were generated representing the range and distribution of the extracted parameters. These matrices serve as statistical models representing tumor-related characteristics. To evaluate the reliability of the analysis approach, a separate set of tumor images referred to as the blind dataset was

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processed using the same preprocessing and feature extraction steps.

The extracted statistical features from the blind dataset were compared with the statistical ranges obtained from the reference dataset. The comparison showed that a majority of the blind dataset images exhibited feature values within the expected statistical range.

The results indicated that more than two-thirds of the blind dataset images satisfied the statistical conditions derived from the reference dataset, demonstrating consistency in the extracted feature patterns.

These findings suggest that the combination of preprocessing, ROI extraction, statistical feature analysis, and texture analysis provides a systematic approach for identifying tumor-related patterns in medical images.

V. Conclusion:

The present research study focused on the analysis of medical images for identifying tumor-related characteristics using statistical and texture-based image processing techniques. Medical imaging plays a crucial role in the early detection and analysis of abnormal tissue structures, and the application of digital image processing methods can assist in extracting meaningful information from medical images for diagnostic support.

In this study, a systematic methodology was developed for analyzing tumor images using a combination of preprocessing, region of interest (ROI) extraction, statistical feature analysis, and texture-based evaluation. The primary objective of the study was to investigate whether statistical parameters derived from digital images could be used to characterize tumor regions and identify patterns associated with abnormal tissue structures.

Initially, the acquired medical images were subjected to preprocessing in order to improve image quality and reduce the effects of noise introduced during the imaging process. Adaptive Mean Filtering was applied to the input image datasets to reduce noise while preserving important structural features. The effectiveness of the filtering process was evaluated using standard image quality parameters such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The obtained results indicated that the filtering process successfully improved image clarity and enhanced the reliability of further image analysis.

After preprocessing, the Region of Interest (ROI) corresponding to the suspected tumor region was extracted from each image. The extraction of ROI is an important step in medical image analysis because it allows the analysis to focus on the relevant tissue region while eliminating unnecessary background information. This step also helps reduce computational complexity and improves the accuracy of feature extraction.

Once the ROI was identified, statistical analysis of the pixel intensity distribution was performed. Several statistical features were calculated to characterize the properties of the tumor region. These features included minimum and maximum pixel intensity values, mean intensity, median intensity, standard deviation, and entropy. Each of these parameters provides quantitative information about the intensity variation and structural characteristics of the tumor region.

The statistical parameters revealed that tumor regions exhibit significant variability in pixel intensity values compared to surrounding tissue regions. The mean and median intensity values provided an indication of the overall brightness level of the tumor region, while the standard deviation represented the variation of pixel intensities within the ROI. Higher variability

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in intensity values suggested the presence of heterogeneous tissue structures, which is often observed in tumor regions.

In addition to first-order statistical features, texture-based analysis was performed using the Gray Level Co-occurrence Matrix (GLCM). Texture analysis plays an important role in medical image processing because it describes the spatial relationship between pixel intensities and helps identify structural patterns within the image. Several texture features were extracted from the GLCM, including contrast, correlation, and homogeneity.

The analysis of GLCM features demonstrated that tumor regions exhibit distinctive texture characteristics due to irregular tissue structures and variations in intensity distribution. Higher contrast values indicated stronger intensity variations between neighboring pixels, while entropy values reflected the complexity and randomness present in tumor textures. Homogeneity values provided information about the uniformity of pixel intensity distribution within the ROI.

After extracting statistical and texture features from the reference dataset, statistical measurement matrices were generated to represent the range and distribution of feature values associated with tumor regions. These matrices served as a reference model for evaluating unknown image samples.

To validate the proposed analysis approach, a blind dataset consisting of tumor images not included in the reference dataset was analyzed using the same methodology. The statistical features extracted from the blind dataset were compared with the measurement matrices derived from the reference dataset.

The comparative analysis showed that a significant proportion of the blind dataset images exhibited statistical characteristics consistent with those obtained from the reference dataset. More than two-thirds of the blind dataset images satisfied the statistical conditions defined by the measurement matrices. This observation indicates that the proposed statistical analysis framework is capable of identifying tumor-related patterns in medical images with reasonable reliability.

The findings of the study demonstrate that statistical and texture-based image analysis can provide useful quantitative descriptors for identifying abnormal tissue regions in medical images. The integration of preprocessing, ROI extraction, and feature extraction techniques forms an effective framework for analyzing tumor images using digital image processing methods.

Although the proposed approach does not perform direct classification of tumor types, it provides a structured analytical method for detecting and characterizing tumor-related patterns within medical images. The methodology can therefore serve as a supporting tool for medical image analysis and may assist healthcare professionals in the interpretation of diagnostic imaging data.

Overall, the results of the study indicate that statistical feature extraction and texture analysis techniques can play an important role in the development of computer-assisted diagnostic systems. These techniques enable the extraction of meaningful information from medical images and contribute to improved understanding of tumor structures and their characteristics.

VI. Future Work:

While the proposed methodology demonstrates promising results in analyzing tumor images, several improvements can be explored in future research. Future studies may involve the use of larger and more diverse image datasets in order to

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Reference ID: IJCS-SI-24 PAGE NO: 001-016

improve the robustness and generalizability of the analysis framework. Advanced segmentation techniques may also be incorporated to improve the accuracy of ROI extraction.

Additionally, machine learning and pattern recognition techniques may be integrated with the extracted statistical features to develop automated tumor detection and classification systems. The use of deep learning models and advanced texture analysis methods could further enhance the accuracy and efficiency of medical image analysis.

Future research may also explore the integration of multimodal medical imaging data, such as combining information from different imaging modalities, to obtain more comprehensive analysis of tumor characteristics. Such developments could contribute significantly to the advancement of computer-assisted medical diagnosis systems.

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