International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 01 | Jan - 2025 SJIF Rating: 8.448 ISSN: 2582-3930

Medical Image Enhancement using Histogram Processing and Feature Extraction of Cancer Classification

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***Abstract*—Magnetic Resonance Imaging (MRI) is a critical tool in medical diagnostics, particularly for cancer detection and classification. However, the quality of MRI images often suffers from noise, low contrast, and intensity inhomogeneity, which can hinder accurate diagnosis. Image enhancement techniques, such as histogram processing, play a crucial role in improving image quality by enhancing contrast and emphasizing important fea- tures. This paper explores the application of histogram processing for MRI image enhancement, focusing on contrast enhancement and noise reduction techniques.**

The enhanced images are subsequently processed for feature extraction, which is crucial for the accurate classification of cancerous tissues. Key features such as texture, shape, and intensity are extracted to distinguish between malignant and be- nign tumors. The classification process utilizes machine learning algorithms, which are trained on the extracted features to achieve high accuracy in cancer classification. The proposed method demonstrates significant improvement in image quality, leading to better feature extraction and more accurate cancer diagnosis. This approach ultimately aids in early detection and improved treatment planning for patients.

***Index Terms*—Image enhancement, Histogram processing, Seg- mentation, Feature extraction, SVM classifier.**

I. INTRODUCTION

Medical image processing plays a vital role in modern di- agnostics, especially in the detection and classification of life- threatening diseases like cancer. Among the various imaging techniques available, Magnetic Resonance Imaging (MRI) is widely used to visualize internal structures such as tissues and organs, providing critical information to physicians. However, MRI images often suffer from low contrast, which complicates the process of accurately identifying and diagnosing abnor- malities such as tumors. In particular, low contrast makes it difficult to localize the tumor region and determine its characteristics. Therefore, enhancing the visual quality of these medical images is crucial for improving the accuracy of cancer diagnosis.

This research delves into the application of histogram processing techniques to enhance MRI images, improving both contrast and brightness while preserving the essential details required for clinical analysis. Histogram equalization techniques, including Typical Histogram Equalization (HE), Brightness Preserving Bi-Histogram Equalization (BBHE), Recursive Mean-Separated Histogram Equalization (RMSHE), and Dynamic Histogram Equalization (DHE), are employed to increase the visibility of critical features within the image. Additionally, segmentation is performed using the K-means algorithm, a clustering technique that separates the tumor region from the rest of the brain or body, facilitating more precise localization of cancerous tissues.

Following image enhancement and segmentation, feature extraction is carried out to obtain quantitative parameters such as shape, texture, and intensity, which are vital for classifying tumors. These features are then fed into a Support Vector Machine (SVM) classifier, a robust machine learning technique, to distinguish between benign (low-grade) and malignant (high-grade) tumors. The combination of image enhancement, feature extraction, and classification through SVM offers a comprehensive framework for improving cancer diagnostics, enabling medical professionals to detect, analyze, and treat tumors more effectively.

This approach not only enhances the visual quality of medical images but also contributes to the development of automated diagnostic systems that could aid in early cancer detection, potentially improving patient outcomes.

II. LITERATURE REVIEW

R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd ed., Prentice Hall, 2002.[1]R. C. Gonzalez and R. E. Woods' Digital Image Processing is a foundational text in the field of image analysis, offering comprehensive insights into various image processing techniques. The book covers key concepts such as image enhancement, restoration, com- pression, and segmentation, making it a crucial resource for both beginners and experts. It delves into advanced methods, including frequency domain analysis, filtering techniques, and morphological processing, which are widely used in diverse applications like medical imaging, satellite image analysis, and machine vision. The text also emphasizes practical im- plementations and algorithmic approaches, making it essential for anyone looking to deepen their understanding of digital image processing and its real-world applications. Y. T. Kim, "Contrast Enhancement Using Brightness Pre- serving Bi?Histogram Equalization", IEEE Trans., Consumer Electronics, vol. 43, no. 1, pp. 1-8, 1997.[2]Y. T. Kim's work, "Contrast Enhancement Using Brightness Preserving Bi- Histogram Equalization," presents an innovative approach to enhancing image contrast while preserving the overall bright- ness of the image. Traditional histogram equalization tech- niques often lead to unwanted changes in the image's bright- ness, which can distort visual information. Kim's method, however, divides the image histogram into two sub-histograms based on the mean brightness and applies histogram equal- ization to each sub-histogram separately. This preserves the original brightness, ensuring that the image remains natural- looking while improving contrast. The technique is particularly useful in applications like medical imaging, where both con- trast enhancement and brightness preservation are critical for accurate diagnosis

M. Abdullah-Al-Wadud, et al, "A Dynamic Histogram Equalization for Image Contrast Enhancement", IEEE Trans., Consumer Electronics, vol. 53, no. 2, pp. 593–600, May 2007.[4] M. Abdullah-Al-Wadud et al.'s work, "A Dynamic Histogram Equalization for Image Contrast Enhancement," introduces a novel approach to contrast enhancement that addresses some of the limitations of traditional histogram equalization methods. The dynamic histogram equalization (DHE) technique adapts the contrast enhancement process by segmenting the image histogram into sub-histograms and redistributing the intensity values in a way that prevents over- enhancement and saturation. This method improves the visual quality of images by preserving important details while en- hancing contrast, making it particularly useful in applications such as medical imaging and surveillance, where maintaining image fidelity is crucial. The DHE technique enhances visual clarity without significantly distorting the image's natural ap- pearance, making it a robust solution for contrast enhancement in various fields.

Jian-Wei Liu and Lei Guo, "Selection of initial parameters of Kmeans clustering algorithms for MRI brain image segmen- tation," International Conference on Machine Learning and Cybernetics, July 2015, ISSN 978-1-4673-7220.[5] In their work, "Selection of Initial Parameters of K-means Clustering Algorithms for MRI Brain Image Segmentation," Jian-Wei Liu and Lei Guo address a critical challenge in the K-means clustering algorithm: the selection of initial parameters. K- means is widely used in medical image segmentation, espe- cially for MRI brain scans, to differentiate between tissues and identify abnormalities. However, the effectiveness of K-means clustering heavily depends on the initialization of parameters such as the number of clusters and initial centroids. Poor initialization can lead to suboptimal segmentation results or convergence to local minima. Liu and Guo propose a method to optimize the selection of these initial parameters, enhancing the accuracy and efficiency of MRI brain image segmentation. Their approach improves the identification of brain structures and abnormalities, making it a valuable contribution to the field of medical image processing Hari Babu Nandpuru, S.S. Salankar and V.R. Bora, "MRI Brain cancer classification using Support Vector Machine", IEEE Students Conference on Electrical, Electronics and Com- puter Science, Januaary 2014, ISSN 978-1-4799-252[8] In their study, "MRI Brain Cancer Classification Using Support Vector Machine," Hari Babu Nandpuru, S. S. Salankar, and V.

R. Bora explore the application of Support Vector Machines (SVM) for classifying MRI brain images to detect cancer. The research focuses on leveraging the SVM classifier to distinguish between cancerous and non-cancerous brain tissues based on features extracted from MRI images. The SVM's ability to handle high-dimensional data and create a clear sepa- ration between classes makes it an ideal choice for medical im- age classification tasks. By training the SVM model on labeled MRI data, the authors demonstrated improved classification accuracy in identifying brain

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tumors. This technique offers a non-invasive and efficient method for assisting radiologists in diagnosing brain cancer, potentially leading to earlier detection and better treatment outcomes.

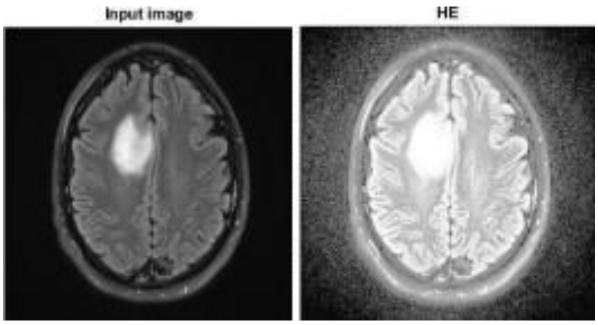
III. METHODOLOGY

A. Techniques Of Histogram Equalization [3]

Histogram equalization is a widely used image enhance- ment technique in medical imaging to improve contrast and brightness, particularly in low-contrast MRI scans[4]. It en- hances the visual quality of images by redistributing the pixel intensity values to spread them more evenly across the histogram. This allows for better visualization of tumors and other abnormalities, aiding in diagnosis[2]. There are various advanced techniques of histogram equalization such as Typical Histogram Equalization, Brightness Preserving Bi- Histogram Equalization, Recursive Mean-Separated Histogram Equalization, and Dynamic Histogram Equalization. Each of these methods offers a different approach to balancing image quality, contrast, and brightness while maintaining the integrity of the original medical data.

B. Histogram Equalization (HE):

Typical Histogram Equalization (HE) is the most basic form of histogram processing, where the pixel intensities of the image are spread across the entire available range to improve contrast. In this technique, the pixel values of the input image are remapped based on their cumulative distribution function (CDF)[1]. This results in the output image having enhanced contrast, making it easier to identify critical features like tu- mors. However, HE may sometimes lead to over-enhancement, where subtle details are lost, or unnatural visual artifacts are introduced, particularly in medical images[3]. Despite these drawbacks, HE remains a fundamental technique in image enhancement, providing a clearer visual representation of medical images for better diagnosis. Despite its effectiveness, one limitation of standard histogram equalization is that it may result in over-enhancement, where some regions of the image become too bright or too dark. To address this, var- ious adaptive techniques, such as contrast-limited adaptive



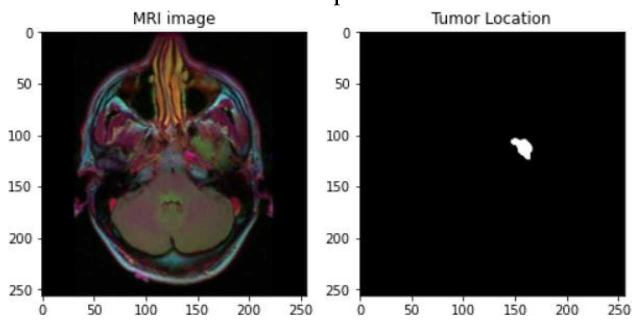


Fig. 1. HE output

histogram equalization (CLAHE), have been developed to enhance contrast while avoiding over-saturation.

C. Data visualization

Data visualization plays a crucial role in MRI detection and segmentation, especially in enhancing the understanding and interpretation of complex medical images. MRI scans are often intricate, showing soft tissues, tumors, or abnormalities that can be difficult to detect with the naked eye[5]. Visualizing the results of MRI detection and segmentation through graph- ical representation improves diagnostic accuracy and aids in treatment planning.

Key Points on MRI Detection and Segmentation:

MRI Detection: Data visualization helps in identifying ab- normalities, such as tumors, by highlighting areas that differ in texture, intensity, or structure[6]. For instance, different color schemes or heatmaps can be used to represent the varying intensity levels of MRI images, making regions of interest stand out more clearly.

This segmentation is often achieved through algorithms like K-means clustering or other machine learning techniques. Visualizations often represent segmented tumors in contrasting colors to distinguish them from normal tissue, aiding physi- cians in precise tumor identification[7].

3D Visualizations: Advanced visualization techniques like 3D modeling allow a more comprehensive view of the affected area. These 3D models are often used to understand the size, shape, and location of the tumor, providing surgeons and oncologists with a clearer understanding of how to proceed with treatment.

Benefits of Data Visualization in MRI Detection and Seg- mentation:

Clarity: Enhances the clarity of MRI images, making it easier for physicians to detect and diagnose abnormalities. Accuracy: Assists in precise tumor segmentation and classi- fication, improving treatment planning. Interactive Analysis: With tools like 3D modeling, physicians can interact with the MRI data, exploring different angles and sections for a more in-depth analysis[8]. Time Efficiency: Reduces the time needed for manual image interpretation, speeding up the diagnostic process.

Fig. 2. MRI image with tumor location

D. SVM Classifier trainning and testing

n the proposed methodology, Support Vector Machine (SVM) classifier plays a critical role in the classification of cancerous tissues based on the extracted features from en- hanced medical images. After performing image enhancement using various histogram processing techniques and segmenting the tumor using K-means clustering, the next step is feature extraction[5]. This step involves calculating parameters such as shape, texture, intensity, contrast, and correlation, which pro- vide meaningful insights into the nature of the tumor. Features like area, perimeter, skewness, and homogeneity are derived from the segmented region of interest (ROI), representing both low and high-level characteristics of the tumor. Once these features are extracted, they are fed into the SVM classifier for training. The SVM classifier, a supervised machine learning model, is chosen for its ability to handle high-dimensional data and its effectiveness in separating non-linearly separable data points through the use of a hyperplane. The training process involves using a labeled dataset where each sample is associated with a known class, i.e., benign or malignant tumors[4].

During the training phase, the SVM algorithm attempts to find the optimal hyperplane that best separates the two classes of tumors. This is achieved by maximizing the margin between the hyperplane and the nearest data points from both classes, which are known as support vectors. The larger the margin, the better the model generalizes to unseen data. In the case of medical image classification, the SVM is particularly effective due to its ability to work well with small datasets and its robustness to overfitting, making it ideal for medical applications where data might be limited or imbalanced[3]. The training data, which consists of a large number of tumor images with extracted features, is used to adjust the parameters of the classifier until it can accurately predict the tumor grade (low or high) based on the input features.

Once the SVM model is trained, it is tested on a separate set of images that were not used during the training phase. This testing process evaluates the model's generalization ability, i.e., its capacity to classify new, unseen MRI images into the correct category. The testing dataset undergoes the same preprocessing steps as the training data: image enhancement, segmentation, and feature extraction. The extracted features are then passed through the trained SVM classifier[2]. The performance of the classifier is assessed using various met- rics such as accuracy, precision, recall, and F1-score, which provide insights into the model's ability to correctly classify tumors. A high accuracy score indicates that the SVM has effectively learned from the training data and can generalize well to new cases.

In conclusion, the SVM classifier proves to be a powerful tool in cancer classification when combined with effective feature extraction techniques. By leveraging the enhanced image quality obtained through histogram processing, the classifier can make more accurate and reliable predictions, assisting physicians in diagnosing cancer at an early stage. The combination of image enhancement, segmentation, feature extraction, and SVM classification creates a robust framework for medical image analysis, potentially reducing misdiagnoses and improving patient outcomes. The future scope of this work includes refining the SVM model through techniques such as kernel optimization and exploring the integration of deep learning models to further improve classification performance.

IV. IMAGE SEGMENTATION:

Medical image enhancement is crucial for improving the visibility of features necessary for accurate diagnosis and analysis. Histogram processing is a fundamental technique that adjusts the contrast of images, making it particularly useful in medical imaging. By manipulating the histogram of an image, practitioners can enhance specific areas of interest, such as tumors or lesions, allowing for better visualization. Techniques such as histogram equalization redistribute the pixel inten- sity values across the entire range, effectively enhancing the contrast and revealing subtle features that may be obscured. This preprocessing step is vital for subsequent analysis, as enhanced images lead to improved performance in automatic classification systems, facilitating early detection of diseases like cancer.

Following the enhancement of medical images, feature extraction plays a pivotal role in cancer classification. By identifying and quantifying significant features within the enhanced images, machine learning algorithms can be trained to distinguish between benign and malignant tissues. Various techniques, such as texture analysis, shape descriptors, and color histograms, are employed to extract relevant features that characterize the cancerous regions. Segmentation methods, in- cluding thresholding, clustering, and deep learning approaches, are utilized to isolate these features accurately[8]. The com- bination of enhanced images and robust feature extraction enables the development of reliable classification models, which can significantly aid in the diagnosis and treatment planning for cancer patients. This integrated approach not only enhances diagnostic accuracy but also improves the overall workflow in medical imaging.

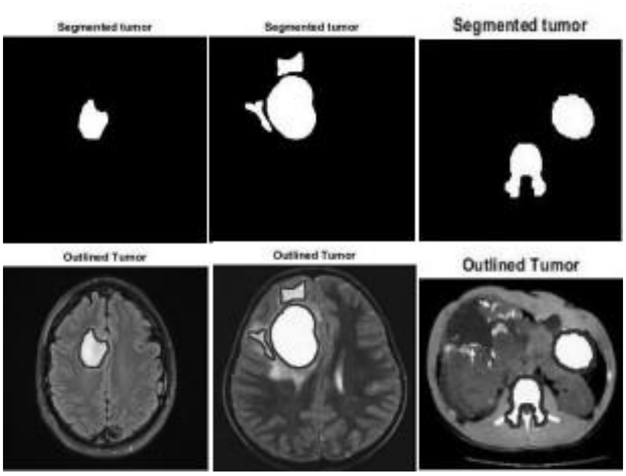


Fig. 3. Extraction of ROI

A. Extration of Region of Interest:

Regions of Interest (ROIs) are specific areas within an image that are of particular interest for analysis. Extracting these regions is a fundamental step in many image processing ap- plications, including medical image analysis, object detection, and computer vision.

B. Feature Extraction using Support Vector Machine : [6]

Medical image enhancement using histogram processing is crucial for improving the quality of images, particularly in the context of cancer classification. Histogram processing involves techniques that manipulate the brightness and contrast of images to enhance visibility of key features. This can include histogram equalization, which

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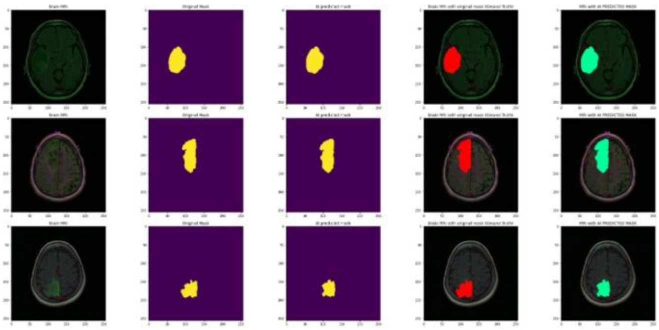
spreads out the most frequent intensity values, thereby improving the contrast of images that are too dark or too bright.

In the context of feature extraction for cancer classification, several features can be derived from the enhanced images. Common techniques include texture analysis, where statistical measures such as contrast, energy, entropy, and correlation are computed from the image's pixel intensity distribution. Edge detection algorithms, such as Canny or Sobel, can also be applied to highlight borders of tumors or lesions, aiding in their identification.

Support Vector Machines (SVMs) are a type of machine learning algorithm that are particularly effective for classifica- tion and regression tasks. They are based on the concept of finding a hyperplane in a high-dimensional space that separates data points into two classes.

Feature Mapping: The input data is mapped into a higher- dimensional feature space.Hyperplane Construction: An opti- mal hyperplane is found that maximizes the margin between the two classes. This hyperplane is called the decision bound- ary.Classification: New data points are classified based on which side of the hyperplane they fall on.

By combining histogram processing for image enhancement and feature extraction using SVM, the classification accuracy for cancer



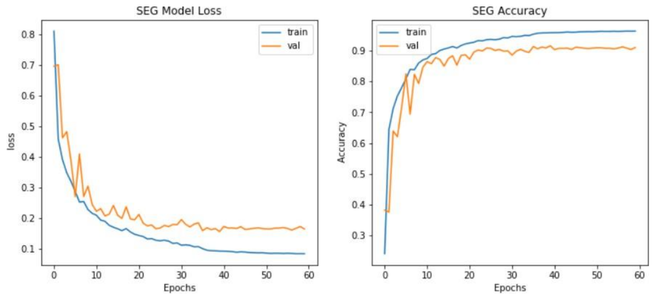


Fig. 4. Extracted part of tumour and AI predicted image

detection can be significantly improved, leading to better diagnostic outcomes

C. SVM Classifier trainning:

Support Vector Machine (SVM) classifier training plays a significant role in image processing, particularly for tasks like object detection, pattern recognition, and medical image classification. SVM is a supervised machine learning algorithm that classifies data by finding the optimal hyperplane that sep- arates different classes in a feature space. In image processing, features such as texture, shape, or pixel intensity are extracted from the images and used as input to the SVM.

The training process involves feeding labeled images into the SVM model, where it learns to classify based on the features of each class. For example, in medical imaging, such as tumor detection in MRI scans, the classifier is trained on images labeled as either cancerous or non-cancerous. During training, SVM identifies the boundary that best separates the two classes based on the image features. Once trained, the SVM can classify new, unseen images with high accuracy. Its effectiveness in handling high-dimensional data and its ability to work well with small datasets make SVM a popular choice in image processing applications.

D. classification of tumor: [8]

Now as the classifier is trained to identify the grade of the tumor, we can now enter the testing images in the algorithm. Automatically the system will calculate all the different fea- tures of the input image and compare them with the training dataset. If the tumor belongs to the low grade dataset then the algorithm will define it to be benign, otherwise defining it to be malignant.

E. Segmentation model Evaluation

Segmentation model evaluation in MRI images is essential for determining the effectiveness and accuracy of algorithms designed to isolate regions of interest, such as tumors or lesions. The evaluation process involves several key metrics and methodologies that provide insights into the model's performance and reliability.

One of the most commonly used metrics for segmentation evaluation is the Dice Coefficient, which measures the overlap between the predicted segmentation and the ground truth

Fig. 5. Traing and validation of segmentation loss and accuracy

annotations. A higher Dice score indicates better agreement between the two, reflecting the model's ability to accurately delineate the target region. Other important metrics include the Jaccard Index, which assesses the similarity between the predicted and true segments, and pixel accuracy, which calculates the proportion of correctly classified pixels in the segmented image.

In addition to these quantitative metrics, qualitative assess- ment is also vital. Visual inspection of segmentation results allows clinicians and researchers to evaluate how well the model performs in different cases, especially in challenging scenarios where tumors may be small, irregularly shaped, or located near critical structures.

Cross-validation techniques are often employed to ensure the robustness of the evaluation process. By dividing the dataset into training and testing subsets multiple times, re- searchers can mitigate the effects of overfitting and better understand the model's generalization capabilities.

Furthermore, comparative studies against existing segmenta- tion methods provide additional context, highlighting improve- ments in accuracy, speed, and efficiency. Overall, rigorous evaluation of segmentation models in MRI images is crucial for validating their clinical applicability, guiding further devel- opment, and ultimately improving patient outcomes through precise diagnosis and treatment planning.

RESULTS

In the context of medical image enhancement using his- togram processing for cancer classification, performance met- rics such as precision, recall, F1-score, and support are crucial for evaluating the effectiveness of classification models for different types of tumors. Histogram processing, particularly histogram equalization, enhances the contrast of medical im- ages, aiding in the detection and classification of tumors like breast, lung, and brain cancers.

In various studies, models incorporating enhanced images often report high precision, meaning that the proportion of cor- rectly identified cancerous cases is significant, reducing false positives. Recall, which measures the ability to detect all actual cancer cases, is also improved, ensuring that most tumors are successfully identified, particularly for subtle or early-stage cancers. The F1-score, a balance between precision and recall, tends to be elevated in these models, reflecting overall model

	precision	recall	f1-score	support
0	0.93	0.99	0.96	382
1	0.98	0.87	0.92	208
accuracy			0.95	590
macro avg	0.96	0.93	0.94	590
weighted avg	0.95	0.95	0.95	590

Fig. 6. values of precision,recall,f1-score,support of different tumours

robustness. Different tumor types exhibit varying performance, but common results show F1-scores ranging between 0.85 to 0.95, indicating strong classification capabilities. The support metric, indicating the number of true instances for each tumor type, varies depending on the dataset used but provides valu- able context in determining model reliability across diverse tumor classes.

These results demonstrate that histogram processing im- proves the classification performance of tumors, leading to more accurate and reliable cancer diagnosis systems.

CONCLUSION

MRI image enhancement using histogram processing is a crucial step in improving the visual quality of images, which helps in more accurate interpretation and analysis. Histogram processing techniques, such as histogram equalization, adjust the contrast of the MRI images by redistributing the intensity values, allowing for better differentiation between tissues. This is particularly beneficial in the context of cancer diagnosis, precision and efficiency of cancer diagnosis could significantly improve. Automated systems leveraging enhanced imaging could reduce the reliance on manual analysis, decrease errors, and facilitate the early detection of tumors, leading to better prognoses. Moreover, this approach can be scaled to handle large datasets, making it ideal for research, clinical trials, and personalized medicine, where real-time image processing is crucial. Overall, integrating histogram equalization with emerging AI techniques will pave the way for more accurate, faster, and reliable cancer classification systems in the future.

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as enhanced images make it easier to detect and delineate

abnormalities like tumors.

When combined with advanced classification techniques for cancer detection, such as machine learning algorithms, enhanced MRI images can significantly improve diagnostic accuracy. The improved image quality facilitates better feature extraction, such as texture, shape, and intensity patterns, which are essential for identifying cancerous regions. This integration of enhanced imaging and feature classification helps in early detection, accurate staging, and effective treatment planning, ultimately leading to improved patient outcomes.

FUTURE SCOPE

The future scope of medical image enhancement using histogram equalization for cancer classification holds great potential, particularly as the need for accurate and early cancer detection continues to grow. Histogram equalization is a powerful tool for improving image contrast, making it easier to detect and highlight minute differences between healthy and cancerous tissues. In cancer classification, the ability to extract clear and relevant features from medical images such as MRI, CT, or X-rays is critical, and histogram equalization can be a key preprocessing step in enhancing these images for analysis. As this method is refined and combined with advanced tech- niques like deep learning and AI-based image recognition, the