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A Research based on Machine Learning Techniques for Brain Tumor and Stroke Detection from MRI Images

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Abstract

Magnetic Resonance Imaging (MRI) is a widely accepted method for providing anatomical information, with research focusing on extending it to provide biological function information. Brain abnormalities, such as neurodegenerative disorders, psychiatric disorders, and aging, are often associated with structural changes in the brain. Brain tumors are the most prevalent abnormality, and their detection from MRI is crucial in medical image processing. Various imaging modalities, including CT, MRI, and PET, are used, with MRI being the most recommended due to its detailed information about the brain. However, detecting tumors from MRIs is a challenging task due to the varying shape and structure of the brain. This research aims to develop an efficient segmentation and classification system using novel image processing techniques, such as Distribution-based Adaptive Median Filtering (DMAF), Skull Removal, Neighborhood Differential Edge Detection (NDED), Intensity Variation Pattern Analysis (IVPA), and Weighted Machine Learning (WML), to improve disease diagnosis and classification.

Keywords: Brain Tumor, Stroke, MRI, Machine Learning, Deep Learning, Image Segmentation, Feature Extraction.

Introduction

Medical image processing is a complex process that involves creating visual illustrations of the inner parts of a body for medical analysis and clinical intervention. This field has been interdisciplinary, involving knowledge from various fields such as biology, physics, medicine, engineering, science, computer, mathematics, and statistics. The study of medicinal images involves interaction of radiation with soft tissue, and the essential environment of the medical imaging system includes processing the imaging systems with energy and analyzing the images by surgeons for efficiency and accuracy [1].

Medical image processing can be pre-analysis or post-analysis operation, and it involves the use of computational resources such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Doppler Ultrasound, and various imaging techniques based on nuclear emission positron emission tomography (PET), single-photon emission computed tomography (SPECT). The main objective of medical image processing is to provide concepts and techniques for automatically analyzing and identifying the human, using computerized algorithms for spatial and temporal analysis to detect patterns [2].

Digital imaging, which involves making digital images such as printed text, manuscripts, and photographs, has made significant progress in the medical field. The approval of Picture

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Archiving and Communication System (PACS) simplifies the distribution, storage, retrieval, and convenient access to images from various modalities, enabling resolution in digital imaging [3].

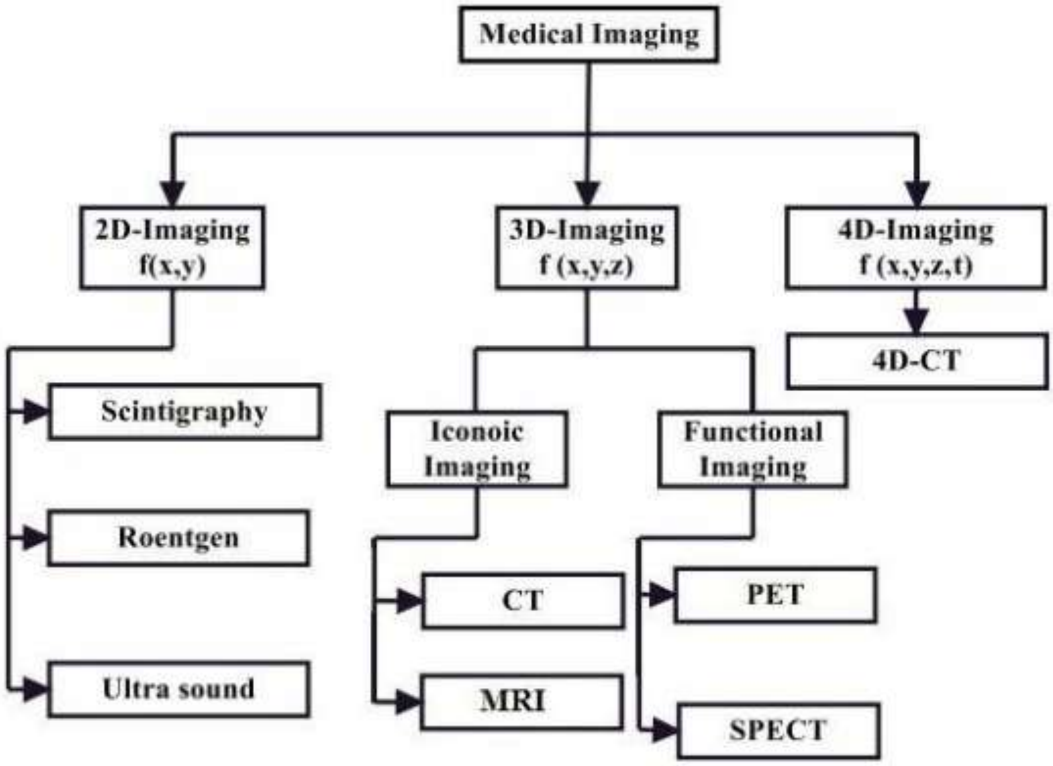

Fig.-1 Overview of image devices vs. Image representations

Image processing is used in areas like biomedical imaging, secured image, pattern recognition, image compression, image retrieval, remote sensing, multimedia, computing, and secured image communication. The components of image processing in medicine cover image forming, picture processing, biomedical signal gathering, and image display for medical diagnosis. Advancements in image processing techniques have allowed for the acquisition of high-quality images for different parts of the body [4].

Medical imaging provides vital information for human health, enabling radiologists, emergency room doctors, and other physicians to diagnose illnesses like cancer, trauma, or pneumonia. Advantages of medical image studies include accurate and quick results, avoiding invasive surgery for cancer and cardiac problems, and monitoring disease progression. Image processing involves various components, including low-level, medium-level, and high-level processes. Digital images have advantages in removing noise, correcting image density, and contrast, and improving diagnostic values. Digital knowhow helps refine patient care and offers cost and workflow assistance to radiology and clinics divisions.

Efficient imaging allows radiologists to review and report patient studies in digital format, centrally available for retrieval on multiple computers, improving workflow, productivity, and reducing costs. It also prevents damage to records, eliminates the need for shuffled files and films, and allows instant access to the entire patient care team.

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Powerful technologies like cloud service for BL sharing, MPDL framework, embedded 3D medical image processing, and tomography imaging offer advantages in disease diagnosis, space, and computation efficiency. Medical image processing needs continuous enhancements to improve the quality of services in the healthcare industry. Techniques for interpolation, image registration, compression, and medical diagnosis need improvement.

Medical image processing techniques are crucial in medical science, as they are used for retrieval, analysis, and modification of biomedical images. Common applications include medical image compression, denoising, retrieval, fusion, filtering, mammograms, and tumor detection. Digital imaging (DIP) plays a significant role in medical imaging, with ultrasonic image processing and X-ray image enhancement being widely used for medical diagnosis. Wavelet noise reduction, point feature matching, and grayscale enhancement improve ultrasonic images, while radioactive isotope and CT enhance X-ray images [5].

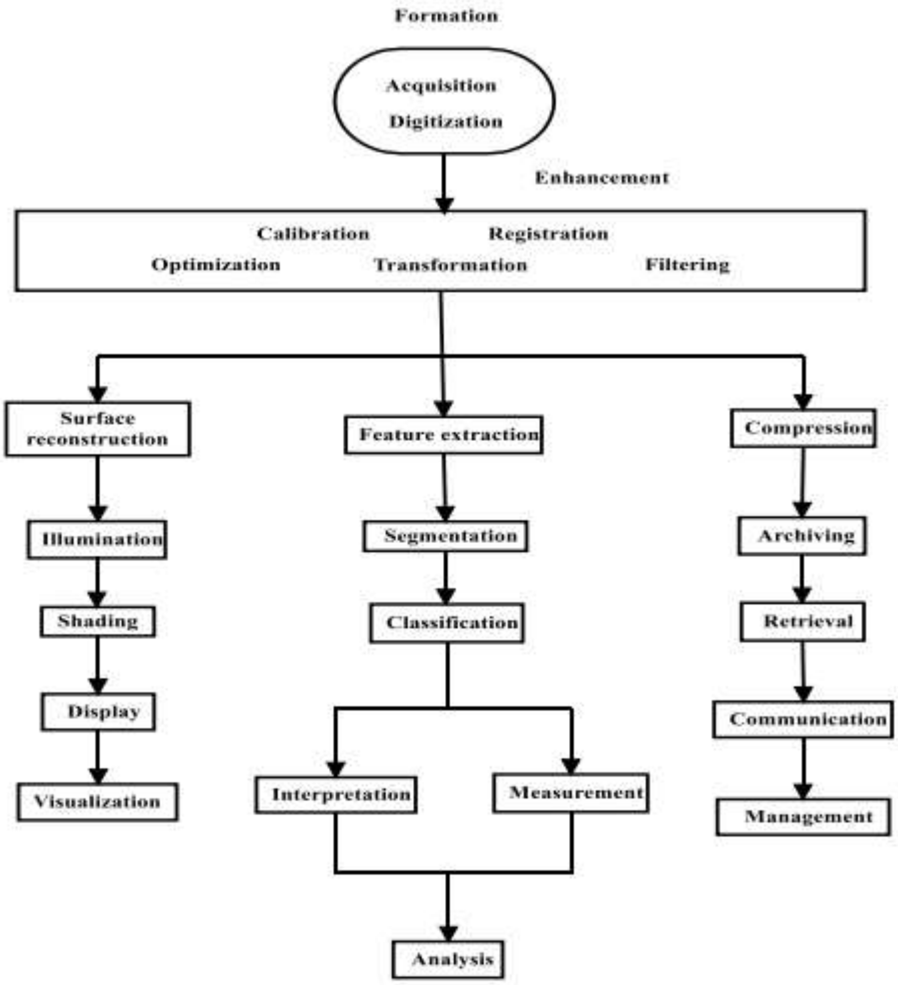

Fig.2 Main components of image processing

MRI is a popular method for classifying brain tumors, as anomalous cells are important for treatment. Data mining and image mining are also involved in medical image processing. Cloud computing and other technologies are being used to leverage power and improve clinical practice and diagnosis. Medical imaging types include Medical Radiography, X-ray imaging, bone densitometry, nuclear imaging, ultrasound, neuroprospaper, magnetic resonance imaging (MRI), computed tomography (CT), fluoroscopy, echocardiography,

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digital vascular imaging, and positron emission tomography (PET) and radio nuclide scanning. MRI measures the effects of magnetic properties of tissue and facilitates assessing brain activity during certain tasks. The imaging process involves forward and inverse Fourier transforms [6].

Biomedical Image Processing is a growing and demanding field, utilizing various imaging methods such as CT scans, X-rays, and MRI to identify the smallest abnormalities in the human body. MRI is safe and reliable, providing sufficient information to detect even the smallest abnormalities. The process of detecting brain tumors from an MRI can be classified into four steps: segmentation, pre-processing, feature extraction, and optimization.

X-ray imaging involves high-frequency waves and electromagnetic spectrum, with radiography being the type of practice. It allows for the partitioning of an image into mutually exclusive regions, known as image segmentation. This process improves the survival rate of patients and treatment possibilities in diagnosing brain tumors. Nuclear imaging is rapidly developing, focusing on the physiological process and treatment evaluation of diseases. It involves the emission of electromagnetic waves within the body, detecting organs through a special camera and computer-generated images. Types of nuclear imaging include bone density scan, cardiac PET sarcoid, cardiac PET viability, cardiac PET perfusion, and cardiac SPECT perfusion. Bone densitometry measures bone loss and is often used to diagnose osteoporosis. Ultrasound imaging produces high-frequency sound waves to scan the internal structure of the body, providing valuable information about illnesses and blood flow. Ultrasound is composed of electromechanical elements and has several modes, including A-mode, B-mode, M-mode, 3D ultrasound, color doppler, audio doppler, and spectral Doppler [7].

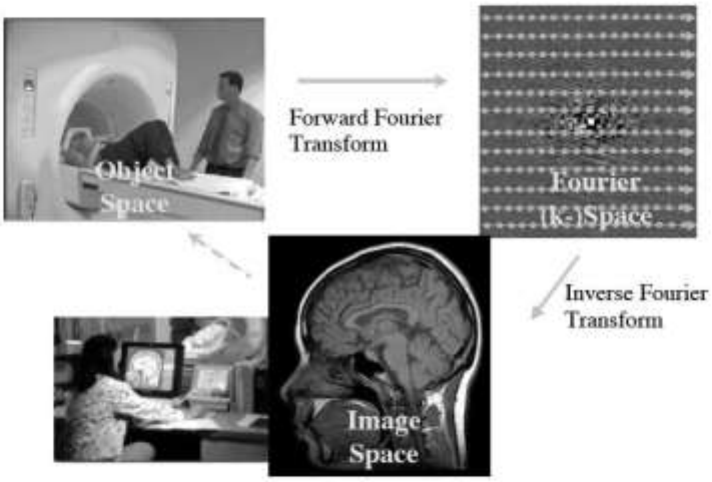

Fig.3 The MR imaging process showed as forward and inverse Fourier transforms

Computed Tomography (CT) is a computer-based technique that uses X-ray measurements to produce cross-sectional specific areas of scanned objects. CT scans generate three-dimensional images inside the human body, allowing for manipulation of soft tissues to enhance bony structures. However, there are risks associated with CT scans and X-rays, including the risk of cancer. CT-based fractional flow reserve (CT-FFR) is better for cardiac catheterization laboratories but is expensive. Fluoroscopy is a real-time process of internal body structures, using fluorescent screens and radiation. It is used in airport security scanners to check hidden bombs and weapons, but has low doses of radiation. Echocardiography uses sound waves to create moving images of the human body, mainly in the heart, providing

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detailed information about heart valves. Digital vascular imaging is an advanced system in image processing that aids in the diagnosis and treatment of cardiovascular diseases and conditions. It uses advanced technology and digital fluoroscopy to segment blood vessels in the heart and blood vessels involved in capillaries, venules, veins, and arteries. Magnetic resonance imaging systems provide highly detailed images of tissue in the body and can be partitioned into multiple segments. Pet and radionuclide scanning is a non-invasive method used to assess the spread of cancers and metabolic activity in the human body. Neuroprospaper is related to biomedical imaging and neuro science, designed as small as possible to be invasive. Magnetic Resonance Imaging (MRI) is used by radiologists to take pictures of anatomy and disease in pathological processes from the human body.

MRI is a more flexible method than CT scans and X-rays, providing three-dimensional images in any direction and depth of the body. It is used in clinics and hospitals and is better than CT scans for staging and diagnosis. MRI has various roles, including neuroimaging, cardiovascular, musculoskeletal, angiography, liver and gastrointestinal, and more.

Brain tumors can occur in any stage, and symptoms depend on type, size, and location. Primary brain tumors originate in the brain and can be benign or cancerous. Common types include meningioma's and gliomas, which develop from nerve cells, glands, brain cells, and the membranes surrounding the brain. Other primary tumors include pituitary tumors, pineal gland cancers, ependymomas, CNS lymphomas, primary germ cells, Schwannomas, and craniopharyngiomas [8].

Secondary brain tumors occur in the brain but spread through other parts like lungs, breast, or kidneys and metastasize to the brain. They can be malignant but not spread from one part to another. Diagnosis of brain tumors starts with physical exams and a medical history. Neurological examinations, including a neurological test, are performed, and the patient's coordination, mathematical ability, memory, and muscle strength are evaluated. Interventions used to diagnose and treat brain tumors include CT scans, MRI scans, skull x-rays, biopsy, and angiography. Brain tumor diagnosis is crucial for reducing long-term disability and saving lives. To diagnose brain tumors, patients are referred to brain specialists and neurologists, who conduct physical examinations, tests, and examine nerve systems. Additional diagnostic tests may include PET scans, SPECT, and EEG to evaluate seizures activity. Segmentation of images is essential in image processing, with methods categorized into manual, semi-automatic, and fully automatic segments. Automatic segmentation is challenging, but semi-automatic methods have been developed for segmenting brain tumors from MR images. Semi-automatic segmentation mainly consists of software computing, providing better results than manual segmentation. Fully-automatic segmentation uses artificial intelligence and prior knowledge to determine tumor segmentation without human interaction. Computer-aided diagnosis (CAD) systems help physicians clarify medical images, such as X-ray, ultrasound, and MRI diagnostic images. CAD is used to diagnose pathological brain detection, lung cancer, breast cancer, coronary artery diseases, congenital heart defects, nuclear medicine, Alzheimer's diseases, and diabetic retinopathy. CAD provides highly accurate diagnosis by using expert endoscopists to take EC images and dye for staining. Accurate segmentation is achieved through various algorithms, including Minimum Distance Classifier (MDC), Cascade Classifier (CC), Nearest Neighbor Rule (NNR), Naïve Bayesian classifier (NBC), Support Vector Machine (SVM), Artificial Neural Network (ANN), Radial Basis Function Network (RBF), and Principle Component Analysis (PCA). In conclusion, brain tumor diagnosis is crucial for reducing long-term disability and saving lives [9].

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Literature Survey

This paper reviews the segmentation methods for detecting brain tumors using clustering and morphological filtering. The focus is on methods such as potential field segmentation, improved tumor cut segmentation, statistical region fusion segmentation, Random Forests (RF) and Conditional Random Fields (CRF) techniques. The authors compare these methods with state-of-the-art methods to determine their superior quality [10].

Medical image processing methods are also discussed, with the Brain Tumor Image Segmentation (BRATS) MRI benchmark database being extensively used. The authors propose K means clustering and filtering with morphological filtering to avoid misclustered regions in medical images. A deep feature fusion methodology for breast cancer diagnosis is presented, addressing concerns of fewer datasets, extended computation time, and wide image preprocessing need. The methodology uses convolutional neural networks (CNNs) with existing radiomic structures to extract low to mid-level features from three modalities.

Greenspan et al. (2016) demonstrate an efficient method for deep learning, improving artificial neural networks with more layers for advanced levels of abstraction and better calculations from data. Convolutional neural networks (CNNs) are shown to be a powerful tool for acquiring mid-level and high-level abstractions, and medical image analysis is introduced into a field where CNNs and other deep learning methods are analyzed to overcome issues [11].

Choi et al. (2013) analyzed the performance of hyper spectral image fusion methods based on contour let, revealing three types of contour let transforms: original contour let transform, non-sub sampled contour let transform, and contour let transform. The last two transforms achieved better results in spatial resolution and conserving spectral information. Sharma et al. (2013) demonstrated effective methods for diagnosing images using CAD-based techniques, such as the ANPOVA method and the genetic algorithm-based feature solution. El-Dahshan et al. (2014) demonstrated the effective detection of cervical cancer using the Neuro Fuzzy Inference System Classifier, using Pap Smear Images for screening and diagnosis.

Baraiya & Modi (2016) examined different approaches for brain tumor extraction from MRI images, comparing the accuracy of diverse segmentation techniques. Mendonça et al. (2014) tackled the challenging task of vascular segmentation in retina, modifying the scope of filters in preprocessing and vessel enhancement. Praveen & Agrawal (2015) proposed a hybrid approach to identify brain tumors and classify MRI images using fast bounding boxes.

In summary, these studies provide valuable insights into the performance of hyper spectral image fusion methods, image diagnosis, and segmentation techniques. The hybrid approaches proposed in these studies aim to improve the accuracy and precision of these methods, particularly in the medical field where image segmentation is crucial for surgical scheduling and medical assessments [12].

The study discusses hybrid approaches for image segmentation, including blood vessel segmentation in retina for diabetic retinopathy detection. A multilayer perception neural network was used for retinal blood vessel recognition, identifying features like hemorrhages

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and exudates. The study also focuses on classifying each pixel in retinal images into vessel and non-vessel categories [13].

Teramoto & Fujita (2013) investigate the detection of lung nodules in chest CT images using a cylindrical nodule enhancement filter. The proposed method includes segmentation of lung region, preprocessing, nodule enhancement, additional segmentation, and false positive reduction. The study found that a lung nodule was detected earlier and with better speed compared to other techniques [14].

Li et al. (2016) proposed a cross-modality approach for better performance without artificially designed features and preprocessing. They proposed a novel supervised method of cross-modality data transformation using a wide and deep neural network. The network output was labeled as the label map of every pixel for a specified image patch, outperforming other methods in terms of sensitivity, specificity, and accuracy.

In medical diagnosis systems (MDS), Magnetic Resonance Imaging (MRI) is preferred due to its ability to accurately capture soft tissues of the inner parts of the human body and visualize finer details. MRI offers advantages such as effective visualization of organ structures, safety, three-dimensional images, and identification of blood flow around organ vessels.

Wu et al. (2017) developed a semiautomatic technique for liver tumor segmentation in CT volumes using fuzzy C-means (FCM) and graph cuts. The technique was tested on 15 CT volumes with different liver lump dimensions. Menze et al. (2015) optimized brain tumor images using the BRATS dataset. Havaei et al. (2017) proposed a fully automatic brain tumor segmentation technique based on deep neural networks, tailored to glioblastomas in MR images [15].

Manocha et al. (2017) implemented automated tumor segmentation techniques for mapping tumor areas, using fuzzy C-means clustering. The work was evaluated using a dataset of T2 weighted images of 15 patients. The fuzzy C-means clustering was used to segment tumors, and the GUI was created for user-friendliness [16].

Sharma & Mukherjee (2014) proposed image segmentation in MRI images using gray level co-occurrence for texture feature selection. Medical resonance imaging (MRI) is a diagnostic method for image segmentation, using techniques such as thresholding, clustering methods, and soft computing techniques. Abdel-Maksoud et al. (2015) proposed a clustering technique using K-means and Fuzzy C-mean clustering techniques to register the least execution time and better accuracy [17].

Patel & Doshi (2014) proposed a segmentation method with clustering approach to detect tumors in brain MRI, recommending MRI due to its lower radiations. Different clustering techniques were reviewed to analyze the best technique for efficient segmentation.

Prastawa et al. (2004) developed an automatic segmentation method for brain tumors, enabling instantaneous detection of edema. This method used non-enhanced T2 MR image channels to improve tissue segmentation. The process involved identifying abnormal regions, determining tissue intensity properties, and detecting edema in abnormal regions. The method was applied to three datasets, representing tumor shapes, location, sizes, image intensities, and enhancements [18].

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Maji et al. (2013) introduced a well-organized classification approach for Additive Kernel SVMs, which offers precision and run-time improvements over linear SVMs. This technique has been applied to various datasets and has been fundamental to various object recognition/image classification schemes [19].

Mustaqeem et al. (2012) focused on brain tumor segmentation, focusing on watershed and threshold segmentation to accurately locate and size tumors. Image acquisition was performed using MRI scan images, and noise-free images were obtained using median filters and high pass filters [20].

Javed et al. (2014) proposed an image fusion technique using local features and fuzzy logic for Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). The method combined essential information from MRI and PET images, resulting in better performance compared to conventional methods [21].

Dhanachandra et al. (2015) used clustering techniques to segment images, using the k means clustering algorithm and subtractive clustering method. Arivazhagan et al. (2013) found instinctive recognition and classification of plant leaf infections using texture features.

The study focuses on the use of multiple classifier systems in plant disease detection and classification. The methodology involves transforming leaf images into HSI format, extracting and analyzing features such as contrast, energy, local homogeneity, shade, and prominence. The study found that the proposed algorithms successfully detected and classified plant diseases with better precision [22].

Woźniak et al. (2014) assessed multiple classifier systems through hybrid systems, focusing on pattern classification by grouping of multi classifier systems. The study highlighted the importance of diversity and decision fusion procedures in producing hybrid classifier systems. Hybridization can be achieved through integrating raw data from various sources, integrating raw data with skilled processes, and integrating with previous skilled knowledge and classification models through machine learning processes [23].

Jermyn et al. (2013) proposed multimodal approaches for optical constraint approximation in near infrared and conservative imaging modalities. However, the technology requires numerous software packages, substantial capability, and time commitment, leading to poor mesh quality for optical image rebuilding. To overcome these issues, the study presented automated digital imaging and communications in medicine image stack segmentation and a novel one-click three-dimensional mesh generator enhanced for multimodal NIR imaging.

Benaichouche et al. (2013) proposed an efficient segmentation method using fuzzy C mean algorithm, which improved the output in three stages: initializing pixel classification, introducing spatial information and mahalanobis, and reclassifying unclassified pixels. Sujji et al. (2013) clarified the thresholding-based method for image segmentation, which involved threshold-based segmentation, edge-based segmentation, region-based segmentation, clustering, and matching [24].

Liu et al. (2014) reviewed graph theoretical methods for segmenting images, categorizing them into several classes: minimal spanning tree-based methods, graph cut-based methods, graph cut-based methods (Markov random field models), and optimal path-based methods.

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The paper also discussed data mining techniques, such as hierarchical clustering, random sampling, and cluster analysis [25].

Kumar et al. (2016) demonstrated the importance of image processing in diagnosing lung cancer using various techniques, including Gabor filter, image segmentation by watershed segmentation, and feature extraction using MATLAB. The watershed segmentation technique showed better results than other segmentation techniques for lung cancer cell recognition.

Ma, Shen et al. (2014) developed a state-of-the-art object-oriented method that combined pixel-based arrangement and segmentation for the classification of polar metric synthetic aperture radar (PolSAR) images. Subasi (2013) designed a new PSO-SVM model for particle swarm optimization (PSO) and SVM to improve EMG signal classification precision. The experimentation involved fragmenting EMG signals into frequency sub-bands using Discrete Wavelet Transform (DWT) and removing statistical feature sets to represent the supply of wavelet coefficients in the recommended method [26].

Verma et al. (2013) discussed edge pattern and brain segmentation for proper diagnosis of brain tumors, highlighting the need for medical image segmentation to solve the complexity in diagnosing brain abnormalities. The research identified segmentation and edge detection foundation as the beginning stage for brain tumor categorizing [27].

Research Methodology

Brain tumors are a significant global health concern, with early detection becoming easier in youth. These tumors are classified into malignant and benign types, with malignant being fast-growing and benign being slow-growing. Digital imaging techniques such as CT scans, MRI, X-rays, SPECT, PET, and ultrasounds are used for early detection. Machine learning (ML) concepts have been applied to image processing and classification of brain tumors.

Malignant gliomas, also known as anaplastic astrocytomas, are considered curative under complete surgical intervention. Grade III and IV gliomas can be treated with radiotherapy, chemotherapy, or a combination thereof. The most malignant form of astrocytoma is glioblastoma, which is rapidly growing and highly malignant [28].

Machine learning involves two main learning stages: supervised learning and unsupervised learning. Supervised learning is used to set training data and responds to the output data, while unsupervised learning explores the set and decreases the dimensionality of information. The learning algorithm is crucial for resolving the problem of detection and diagnosis.

The proposed system consists of three stages: pre-processing, clustering, segmentation, and classification. The first stage involves removing noise and histogram equalization using Distribution based Adaptive Median Filtering (DAMF), Neighborhood Differential Edge Detection (NDED), clustering tumors, Intensity Variant Pattern Analysis (IVPA), and Weighted Machine Learning (WML) classification. The machine learning classifier provides the training set for the image to be classified as normal or abnormal.

The text describes various filters used to reduce noise and smooth images, including convective smoothing, crimson speckle removal, laplacian of Gaussian filter, and unsharp filter. These filters are useful for high frequency blur images and sharpening boundaries in

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printing industries and photography. However, they also have disadvantages such as reducing additive noise, smoothing, and skull from the image [29].

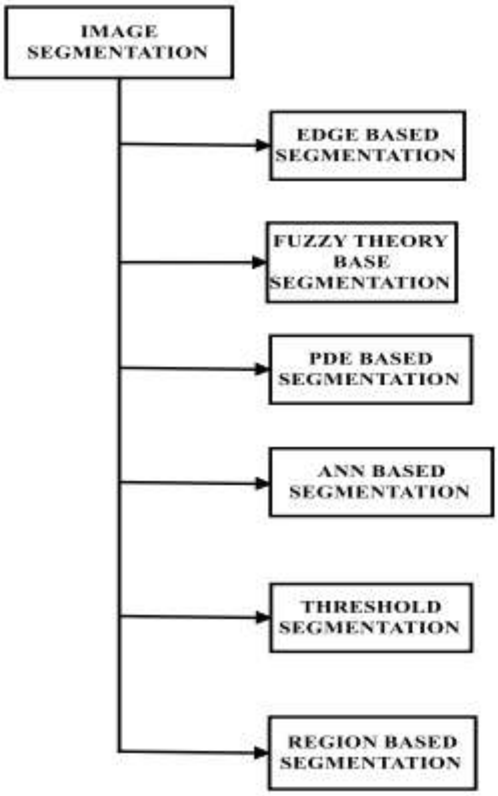

Fig.4 Image segmentation types

Adaptive median filtering is a progressive method related to standard median filtering that categorizes pixels as noise by matching each pixel in the image to its adjacent neighbor pixels. The space of the neighborhood is adaptable, and the threshold for association is set. A pixel altered from a mainstream of its neighbors or not physically associated with those pixels is labeled as impulse noise. These noise pixels are exchanged by the median pixel value of the pixels in the area that has approved the noise labelling test [30].

The adaptive median filter is the basic filter for distribution-based adaptive median filter (DAMF), which integrates the DAMF. In medical imaging applications, preprocessing is essential and demanding, as the original image contains noise and artifacts that disturb the quality of the image. Distribution-based Adaptive Median Filtering (DAMF) is used to eliminate additive noise and skull from the given image. This technique is integrated with the standard medical filtering technique, which performs the filtering operation based on the Gaussian distribution function [31].

Input images of brains are initialized, and the appropriate pseudocode is used to calculate the index of the image based on the lowest and highest pixel intensity values. The maximum area of components among the overall image is known, and the variance from the maximum labeled matrix and normalized pixel value is estimated.

Clustering is a crucial aspect of unsupervised learning, aiming to structure unlabelled data into groups. There are two types of clustering: distance-based clustering and conceptual clustering. Distance-based clustering classifies data into four groups based on distance, while

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conceptual clustering defines common entities from two or more entities. The goal of clustering is to define the inherent grouping with unlabelled data, reduce data, and label properties of natural data types [32].

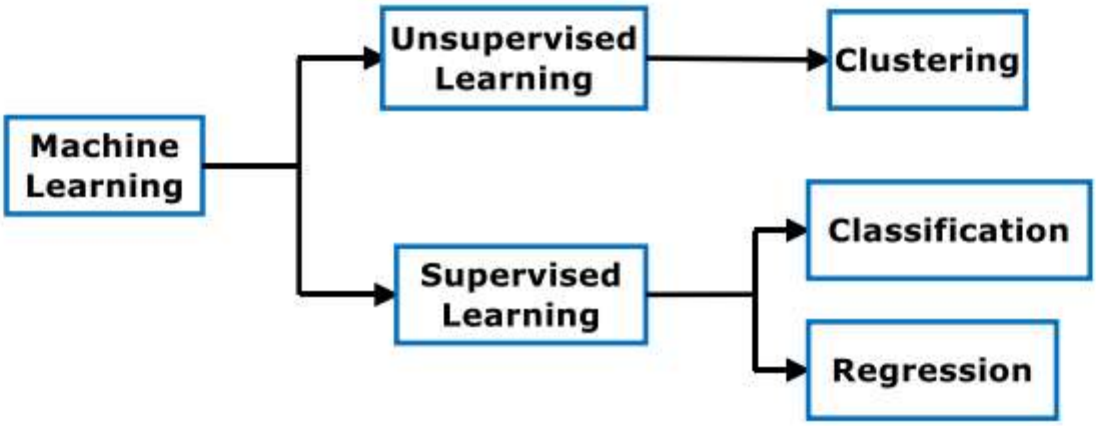

Fig.5 Machine Learning Types

Edge detection is a method used to detect sharp changes in image illumination, such as variations in scene clarity, material properties, surface alignment, and confusion in depths. It involves image analysis, computer vision techniques, pattern recognition, and image processing. Edge detection properties are divided into viewpoint dependent and viewpoint independent [33].

Edge detection usually has three types: diagonal, vertical, and horizontal edges. Diagonal edges are either vertical or horizontal, while vertical edges are detected by the operator of horizontal gradient. Horizontal edges produce vertical edges in the picture, enhancing vertical gradient detection when gradient values are normalized and shifted.

Detecting edges helps in enhancing the sharpness of an image by enhancing the areas covered by the edges. Masks for edge detection include Robinson Compass Masks, Prewitt Operators, Kirsch Compass Masks, Sobel Operators, and Laplacian Operators. Filters can be smoothing or linear filters. Sharpening is a reverse process of blurring, where the edge content decreases while increasing. To sharpen an image, it is necessary to find the edges first and add them to the image.

The NDED technique is used to perform clustering for grouping tumors affected pixels in a skull removed image based on intensity difference analysis and pattern estimation. The algorithm initializes the pre-processed image Y with a (3x3) matrix, computes the mean value, and projects the window over the matrix Tm. Based on variations in neighboring pixels, it is grouped into a cluster.

The intensity variation pattern analysis is used to segment tumors affected pixels, dividing an image into sub-parts for further processing. The accuracy of the image processing system depends on the process of segmentation. The maximum intensity of the image is estimated to locate the tumors spot, and the pattern of the clustered data is extracted and its histogram represented to analyze the tumors level of the image.

The algorithm uses the clustered output image I c as input, initializes a 5x5 window,

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estimates the difference from the center to the neighboring pixels at various angles, calculates the index of the difference matrix, extracts the pattern, and estimates the feature vector F from the histogram of the extracted pattern.

In summary, the NDED technique is used for clustering tumors affected pixels in skull removed images using intensity difference analysis and pattern estimation. This method addresses issues such as robustness, efficiency, scalability, and stability in pattern analysis.

Histogram computation is a data design tool that shows the shape, relative frequency, and centering of information. It is used to understand the output specifications and target customers for all requirements. The histogram has seven basic quality controls and is often confused with bar charts. It is used for continuous data and is used for clustered images of input.

Algorithm III – Intensity Variation Pattern Analysis (IVPA) is an algorithm that uses histogram concepts to estimate the feature vector. It involves counting the number of data points, defining the range of sample, defining the number of class intervals, regulating the interval class thickness, and improving the database or table to each interval.

Skull removal is a surgical process that removes part of the skull to expose the brain. This process can be segmented accurately in image processing using histogram computation and skull removal. The algorithm uses IVPA techniques to extract patterns from the histogram and estimate the feature vector.

Weighted machine learning classification is a process that predicts the class of given information points, also known as labels or targets. It uses binary classifiers to approximate mapping functions, input variables, and output variables. Classification has applications in target marketing, medical diagnosis, and credit approval. There are two types of learners: lazy learners and easy learners. Lazy learners collect input data and wait for output data to perform, while easy learners have classification models based on the given training set before receiving it from classifiers.

Classification algorithms in machine learning are supervised approaches that learn to classify new observations and input data. These algorithms can be bi-class or multi-class, and can be classified into two types: statistical and structural. Some of the classified machine learning algorithms include linear classifiers (Naïve Bayes, logistic regression), decision trees, artificial neural networks, boosted trees, k-nearest neighbors, random forest, and support vector machines [34].

Decision trees are used for regression or classification models, using an exhaustive and mutually exclusive rule set. They can handle both numerical and categorical information and can overfit if there are too many branches. Naive Bayes classifiers are simple probabilistic classifiers based on Bayes' theorem, with strong independence assumptions. Random forests are fast, resistant to overfitting, and have good performance in high-dimensional data.

Artificial neural networks are connected with input/output units and have weights to start with. They can represent real-time applications and provide better results with input/output values. K-nearest neighbors are lazy learning algorithms that store corresponding training information in n-dimensional space.

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Classification models in machine learning have performance and cost functions such as accuracy, sensitivity or recall, specificity, precision, and ROC curve. The classification-based WML techniques are used to classify tumors into normal or abnormal. The algorithm uses a feature vector F, training feature F train, and label Lb as inputs. The normalized value of the feature vector is estimated, and the weight vector W x and W y are assigned based on the angle of θ x and θ y. The location is identified based on the peak points of H 1 and H 2, and the x and y coordinates are estimated. The Root Mean Square (RMS) value for the weight is calculated, and the coordinates, weight matrix, and angle are updated. The final class results are obtained based on the index of minimum RMS (Root Mean Square) value.

A brain tumor segmentation method using one-class Support Vector Machine (SVM) has been proposed, which can learn the nonlinear distribution of image data without prior knowledge. Researchers have used a high number of MRI modalities to create voxel-wise intensity-based feature vectors, which they classified by SVM. Relevance Vector Machine (RVM) classification techniques are proposed and applied to brain images, with the main objective of providing excellent outcomes for MRI brain cancer classification using RVM. The advantages of these methods include increased classification accuracy, sufficient interpretability, and reduced complexity and time consumption [35].

Analysis Report

The research focuses on brain tumor detection, which has great potential in clinical medicine. However, the main challenges in automatic tumor detection are due to the heterogeneity of brain tumors, their deformation, and the weakening of healthy brain sagittal symmetry. Magnetic Resonance Imaging (MRI) is an advanced medical imaging technique used for treating brain tumors. Image segmentation is crucial for accurate quantification of specified areas. However, limitations such as over-segmentation, increased complexity, and time consumption have been observed.

The objective of this work is to develop an efficient segmentation and classification system for MRI brain tumor detection. The proposed system preprocesses images by eliminating additive noise in the given MRI using Distribution based Adaptive Median Filtering (DAMF), Neighborhood Differential Edge Detection (NDED), Intensity Variation Pattern Analysis (IVPA), and Weighted Machine Learning (WML) techniques.

Experiments were carried out on real patient data obtained from the 2013 brain tumor segmentation challenge (BRATS2013). The dataset consisted of three sub-distributes: training, test, and leaderboard. The model iterates over about 2.2 million examples of tumorous patches and 3.2 million of healthy patches.

Performance measures used for results evaluation include Sensitivity, Specificity, Accuracy, Precision, Recall, Jaccard Coefficient, Dice Coefficient, Kappa Coefficient, False Acceptance Rate (FAR), False Rejection Rate (FRR), Genuine Acceptance Rate (GAR), and Receiver Operating Characteristics (ROC).

Specificity measures the proportion of negatives correctly identified as such, defined as the ratio of true negative results to the sum of true negatives and false positives. Accuracy refers to the closeness of a measured value to a standard or known value, and can be referred to as a weighted arithmetic mean of Precision and Inverse Precision, as well as a weighted arithmetic

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mean of Recall and Inverse Recall. Precision is the fraction of retrieved instances that are relevant to the query, and it is estimated based on the ratio of true positive to the sum of true positives and false positives. Recall is the fraction of relevant instances that are retrieved, also known as sensitivity, and offers the most accurate results for detection. It is calculated as the ratio of true positives and the sum of true positives and false negatives.

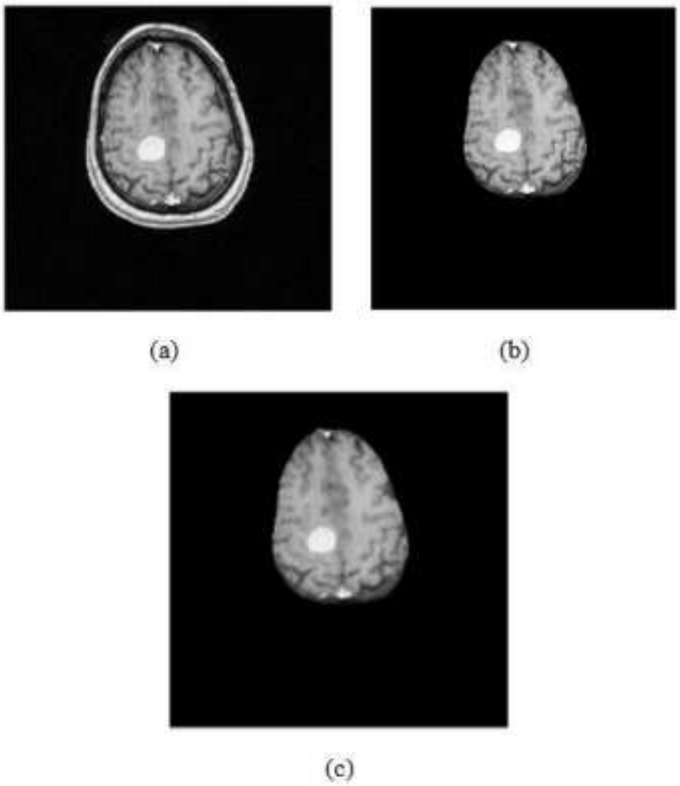

Fig.6 (a) Input Image (b) Normalized image (c) Filtered Image

The Jaccard Coefficient measures asymmetric information on binary variables, considering matching items in which the negative value is not necessary and counting the non-existence value becomes unnecessary. The Dice Coefficient measures accuracy using the statistics precision p and recall r, and the Kappa Coefficient measures inter-rate agreement for qualitative items.

In summary, specificity, accuracy, precision, recall, Jaccard coefficient, Dice coefficient, and Kappa coefficient are essential components of information retrieval algorithms. Each of these factors plays a crucial role in determining the accuracy and efficiency of the segmentation process.

The performance analysis of the proposed Intensity Variation Pattern Analysis using Weighted Machine Learning (IVPA-WML) approach is evaluated and compared with existing approaches. Two techniques, Support Vector Machine (SVM) and Relevant Vector Machine (RVM), are compared with the IVPA-WML based on parameters.

SVM is a discriminative classifier defined by a separating hyper-plane, while RVM is a machine learning technique that uses Bayesian inference to obtain parsimonious solutions for regression and probabilistic classification. The IVPA-WML technique shows a significantly high sensitivity compared to the existing SVM and RVM techniques, with an increase of

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13.63% in sensitivity and a 13.63% increase in specificity. In terms of accuracy, the proposed IVPA-WML technique has a higher accuracy than the existing SVM and RVM techniques. The SVM technique has an accuracy of 87.09, while the RVM technique has a sensitivity accuracy measure of 88.70. The IVPA-WML technique shows an increase of 7.56% in accuracy when compared to the RVM technique.

The results of the comparison show that the proposed IVPA-WML technique has a higher accuracy than the existing SVM and RVM techniques. This indicates that the proposed IVPA-WML technique can be used as a more effective and efficient method for image processing.

The study evaluates the effectiveness of image segmentation using precision and recall. The precision rate of the existing SVM, RVM, and IVPA-WML techniques is compared, with the proposed IVPA-WML technique showing a higher recall rate of 92.95 compared to the existing SVM and RVM techniques. The recall rate of the proposed IVPA-WML technique is significantly higher than the existing SVM and RVM techniques, with an increase of 13.63%. Similarity coefficients such as Jaccard, Dice, and Kappa are used to evaluate the similarity level of the segmented image by the segmentation technique. The study concludes that the proposed IVPA-WML technique has a higher Jaccard coefficient value compared to the existing SVM and RVM techniques.

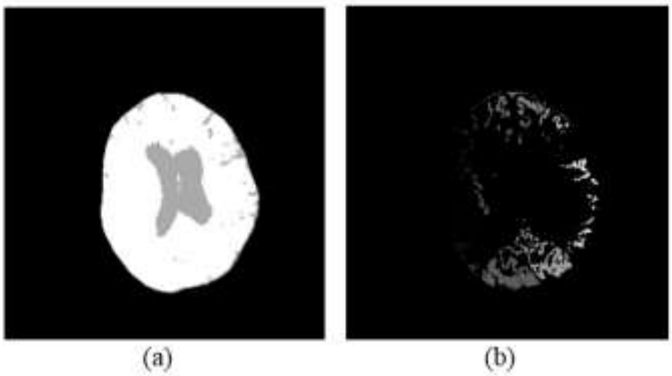

Fig.7 (a) Initial cluster (b) Labelled cluster

The study compares the performance of existing SVM, RVM, and IVPA-WML techniques. The Dice coefficient value of the proposed IVPA-WML technique is significantly higher than the existing SVM and RVM techniques, with a 13.63% increase. The Kappa coefficient value of the proposed IVPA-WML technique is also higher than the existing SVM and RVM techniques.

The False Acceptance Rate (FAR) and False Rejection Rate (FRR) are also evaluated. The proposed IVPA-WML technique has an optimum False Rejection Ratio of 4.0323 for Class 1 and 0 for Class 2, indicating its effectiveness compared to traditional methods. The Genuine Acceptance Rate (GAR) is obtained by combining both FAR and FRR, with a GAR of 95.96 for Class 1 and 100 for Class 2, indicating its effectiveness.

The ROC plot of the true positive rate against the false positive rate for all possible systems calculates the entire performance of the tumor segmentation and classification system. The ROC of the proposed IVPA-WML technique is higher than the existing SVM and RVM.

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Overall, the proposed IVPA-WML technique offers a more effective and efficient method for tumor segmentation and classification.

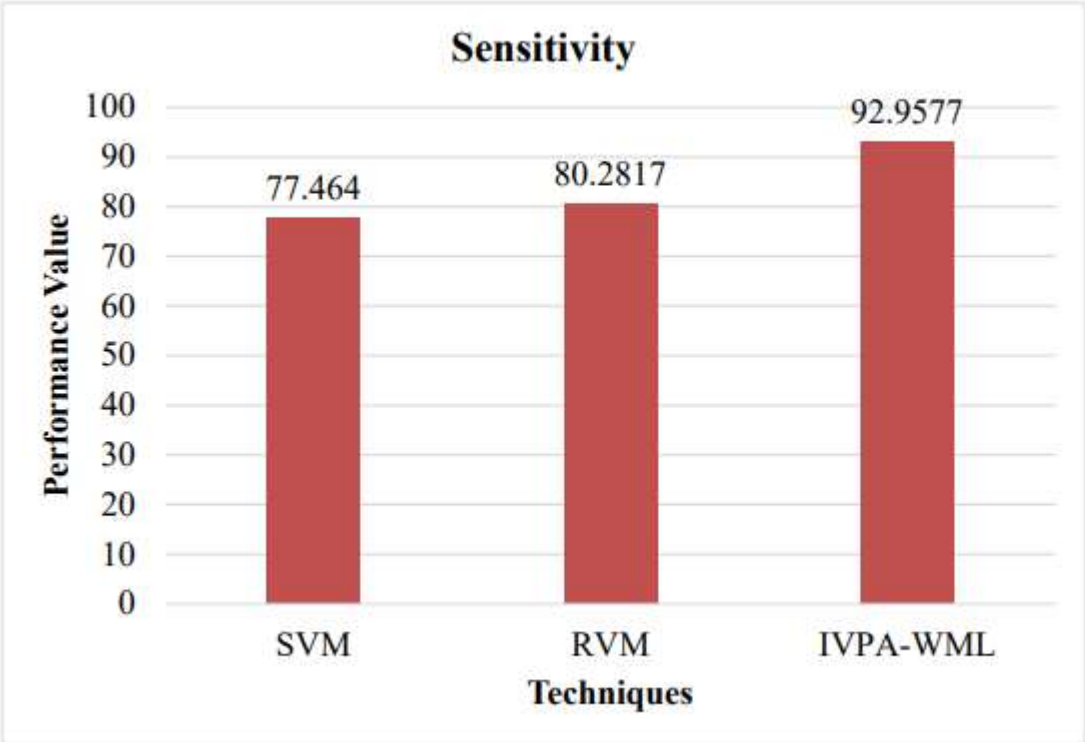

Fig.8 Comparative Analysis of Sensitivity Measure

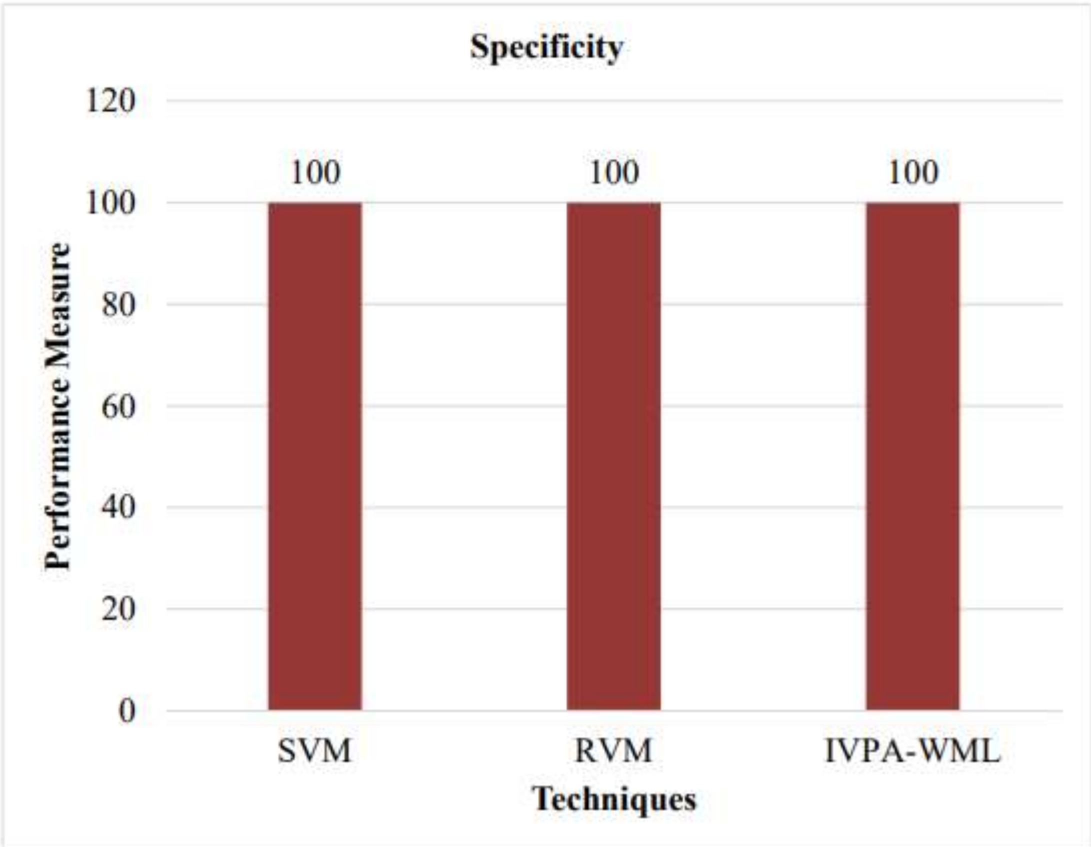

Fig.9 Comparative Analysis of Specificity Measure

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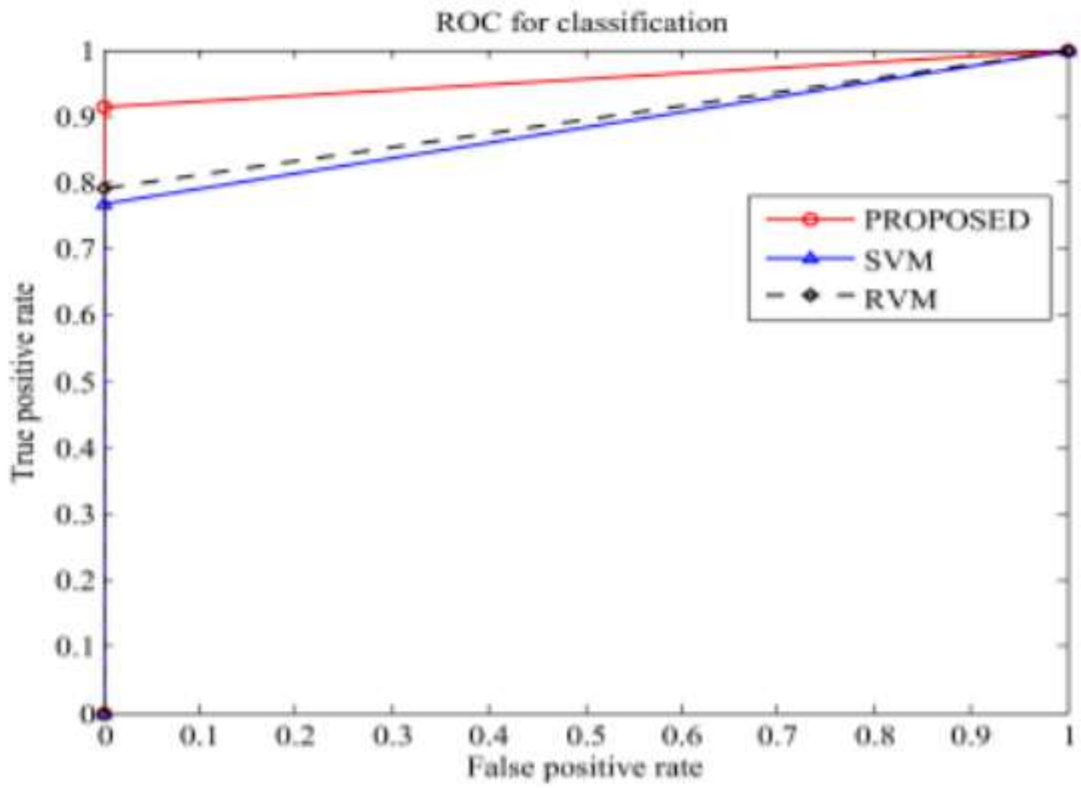

Fig. 10 Shows the ROC Classification Curve

The study compares existing and proposed classification techniques based on measures of Dice, Sensitivity, and Specificity. Various Convolutional Neural Networks (CNN) classification techniques are evaluated. The results show that the proposed Intensity Variant Pattern Analysis-Weighted Machine Learning (IVPA-WML) technique has a high Dice value compared to all existing methods. It also has a high Sensitivity value compared to all existing methods. The proposed IVPA-WML has a high Specificity value compared to all existing methods.

Various parameters such as latitude offset, geocentric translation file, longitude offset, Easting offset, Vertical offset file, and Bin grid origin are also evaluated. The results show that the proposed IVPA-WML technique performs significantly well compared to existing techniques, demonstrating its inherent superiority. The outcomes prove that the proposed methodology is more efficient when compared to existing ones. Similarity coefficients such as Jaccard, Dice, and Kappa are used to compare the proposed technique with existing techniques. Additionally, parameters such as False Acceptance Ratio (FAR), False Rejection Ratio (FRR), and Genuine Acceptance Ratio (GAR) are evaluated for the proposed system. Overall, the results demonstrate the effectiveness of the proposed IVPA-WML technique in MRI brain tumor detection.

Conclusion

This research presents an efficient segmentation and classification system for MRI brain tumor detection, focusing on achieving efficient detection compared to manual methods. The system uses various image processing techniques, including Intensity Variation Pattern Analysis-Weighted Machine Learning (IVPA-WML), to segment tumor regions based on

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intensity and texture patterns. The proposed system uses the BRATS2013 dataset, with training and testing datasets containing 30 and 25 patient subjects. The system also separates the skull region efficiently to avoid misclassified results.

The performance of the proposed system is evaluated using various performance measures, including sensitivity, specificity, accuracy, precision, recall, similarity coefficients, False Acceptance Ratio (FAR), False Rejection Ratio (FRR), and Genuine Acceptance Ratio (GAR). The IVPA-WML technique provides better precision and recall compared to other techniques. The proposed structure concentrated machine learning algorithm is used to find brain tumors with high classification accuracy and minimum time consumption. Future research can enhance the system by implementing this segmentation technique for predicting various types of abnormality levels of brain tumors, performing feature reduction, and using deep learning approaches for intense training. Additionally, feature selection techniques and algorithms are proposed to detect tumor tissue.

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