RESEARCH PAPER

Study and Analysis of Brain Tumor and Stroke Detection using MRI Images and Artificial Intelligence

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ABSTRACT

Magnetic Resonance Imaging (MRI) is a well-established technique for delivering anatomical data, with ongoing research aimed at enhancing its capacity to convey biological function information. Brain abnormalities, including neurodegenerative diseases, psychiatric disorders, and ageing, frequently correlate with structural alterations in the brain. Brain tumours are the most common type of abnormality, and finding them with an MRI is very important in medical image processing. CT, MRI, and PET are some of the imaging techniques that are used. MRI is the best because it gives the most detailed information about the brain. Nonetheless, identifying tumours via MRIs is difficult because the brain's shape and structure are different in each person. This study seeks to create an effective segmentation and classification system through the application of innovative image processing methods, including Distribution-based Adaptive Median Filtering (DMAF), Skull Removal, Neighbourhood Differential Edge Detection (NDED), Intensity Variation Pattern Analysis (IVPA), and Weighted Machine Learning (WML), to enhance disease diagnosis and categorisation..

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

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INTRODUCTION

Medical image processing is a complicated process that makes pictures of the inside of a body for medical analysis and treatment. This field has been interdisciplinary, drawing from biology, physics, medicine, engineering, science, computer science, mathematics, and statistics. The study of medicinal images encompasses the interaction of radiation with soft tissue, and the fundamental environment of the medical imaging system involves the processing of imaging systems with energy and the analysis of images by surgeons for efficiency and accuracy [1].

Medical image processing can happen before or after an analysis, and it uses computers to do things like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Doppler Ultrasound, and different imaging methods based on nuclear emission positron emission tomography (PET) and single-photon emission computed tomography (SPECT). The primary aim of medical image processing is to furnish methodologies and techniques for the automated analysis and identification of humans, employing computerised algorithms for spatial and temporal analysis to discern patterns [2].

Digital imaging, which includes making digital images like printed text, manuscripts, and photographs, has come a long way in medicine. The Picture Archiving and Communication System (PACS) is now approved, which makes it easier to share, store, get back, and easily access images from different modalities. This makes it possible to resolve issues in digital imaging [3].

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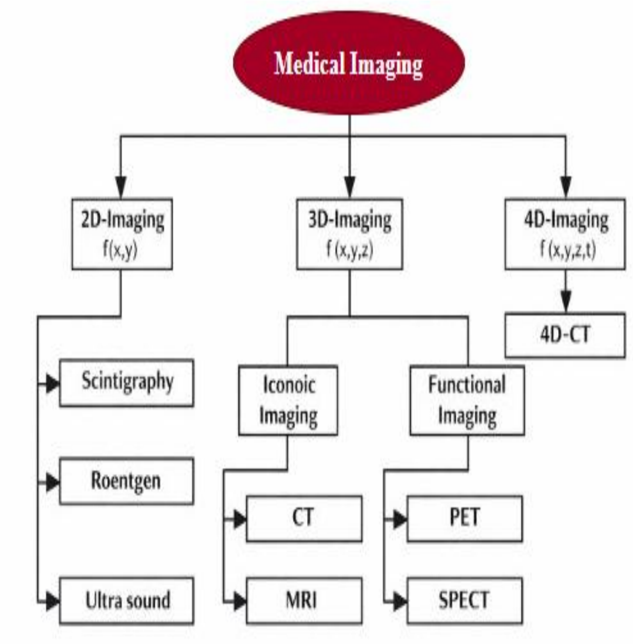

Fig.-1 Concept of medical imaging

Image processing is used in many fields, such as biomedical imaging, secure image communication, remote sensing, multimedia, computing, and pattern recognition. Image processing in medicine includes making images, processing pictures, collecting biomedical signals, and showing images for medical diagnosis. Improvements in image processing methods have made it possible to get high-quality pictures of different parts of the body [4].

Medical imaging gives doctors important information about people's health. For example, it helps radiologists, emergency room doctors, and other doctors figure out what is wrong with someone who has cancer, trauma, or pneumonia. Medical image studies have many benefits, such as getting quick and accurate results, not having to have surgery for cancer or heart problems, and keeping an eye on how a disease is getting worse. There are different parts to image processing, such as low-level, medium-level, and high-level processes. Digital images are better at getting rid of noise, fixing image density and contrast, and making diagnostic values better. Digital know-how helps improve patient care and makes things easier for the radiology and clinic divisions by cutting costs and streamlining work. Radiologists can review and report on patient studies in digital format that is available from a central location on multiple computers. These speeds up work, increases productivity, and lowers costs. It also protects records from damage, gets rid of the need for shuffled files and films, and makes it easy for the whole patient care team to get to them right away.

Cloud service for BL sharing, the MPDL framework, embedded 3D medical image processing, and tomography imaging are all powerful technologies that help with disease diagnosis, space, and computation efficiency. To make healthcare services better, medical image processing needs to be improved all the time. Interpolation, image registration, compression, and medical diagnosis methods need to get better.

Medical image processing techniques are very important in medicine because they are used to get, analyse, and change biomedical images. Some common uses are compressing, denoising, retrieving, fusing, filtering, mammograms, and finding tumours in medical images. Digital imaging (DIP) is very important in medical imaging. For example, ultrasonic image processing and X-ray image enhancement are both commonly used to make medical diagnoses. Wavelet noise reduction, point feature matching, and greyscale enhancement make ultrasonic images better. Radioactive isotope and CT make X-ray images better [5].

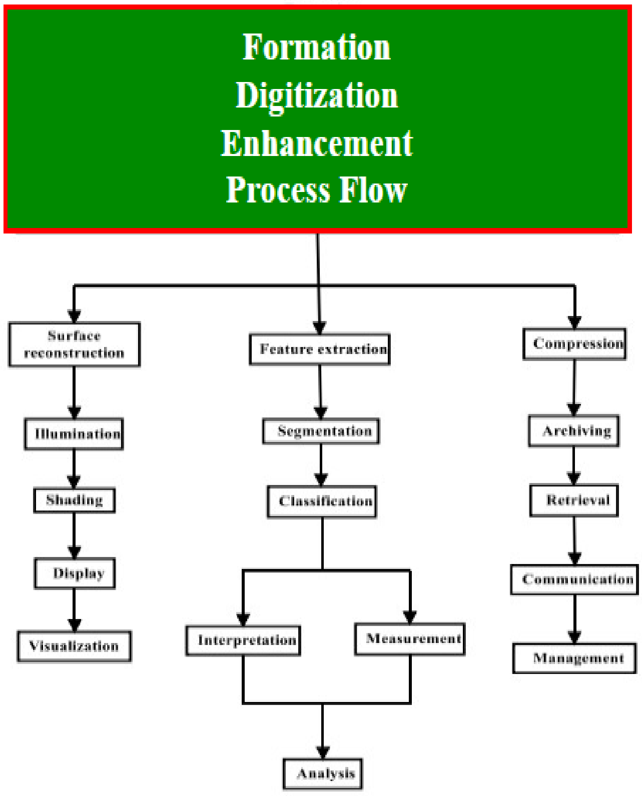

Fig.2 Steps of image processing

MRI is a common way to tell what kind of brain tumour someone has because it's important to know what kind of cells are not normal for treatment. Medical image processing also uses data mining and image mining. Cloud computing and other technologies are being used to make the most of power and make clinical practice and diagnosis better. There are many types of medical imaging, such as medical radiography, X-ray imaging, bone densitometry, nuclear imaging, ultrasound, neuroprospaper, magnetic resonance imaging (MRI), computed tomography (CT), fluoroscopy, echocardiography, digital vascular imaging, positron emission tomography (PET), and radio nuclide scanning. MRI measures how magnetic properties of tissue affect the brain and makes it easier to see how the brain works when doing certain tasks. The imaging process uses both forward and inverse Fourier transforms [6]. Biomedical Image Processing is a growing and important field that uses CT scans, X-rays, and MRIs to find even the smallest problems in the body. MRI is safe and dependable, giving doctors enough information to find even the smallest problems. There are four steps to finding brain tumours on an MRI: segmentation, pre-processing, feature extraction, and optimisation.

Radiography is the type of practice that uses high-frequency waves and the electromagnetic spectrum to take pictures of things. It lets you split an image into parts that don't overlap, which is called image segmentation. This process increases the chances of patients surviving and the options for treating brain tumours. Nuclear imaging is growing quickly and is mainly used to look at how diseases work and how well treatments are working. It involves sending electromagnetic waves through the body and using a special camera and computer-generated images to find organs. There are different kinds of nuclear imaging, such as cardiac PET viability, cardiac PET perfusion, and cardiac SPECT perfusion. Bone densitometry is a test that checks for bone loss and is often used to find out if someone has osteoporosis. Ultrasound imaging uses high-frequency sound waves to look inside the body and give doctors important information about illnesses and blood flow. Ultrasound is made up of electromechanical parts and can work in different ways, such as A-mode, B-mode, M-mode, 3D ultrasound, colour doppler, audio doppler, and spectral Doppler [7].

Computed Tomography (CT) is a computer-based method that uses X-rays to make cross-sectional images of specific areas of scanned objects. CT scans make three-dimensional images of the inside of the body, which lets doctors move soft tissues around to improve bony structures. But CT scans and X-rays can be dangerous, and one of the risks is cancer. CT-based fractional flow reserve (CT-FFR) is better for cardiac catheterisation labs, but it costs a lot. Using fluorescent screens and radiation, fluoroscopy lets you see inside your body in real time. It has low levels of radiation and is used in airport security scanners to look for hidden bombs and weapons. Echocardiography uses sound waves to make moving pictures of the body, mostly the heart, and it gives a lot of information about the heart valves. Digital vascular imaging is a cutting-edge image processing system that helps doctors figure out what's wrong with your heart and blood vessels and how to fix it. It uses digital fluoroscopy and other advanced technology to break down blood vessels in the heart and blood vessels that are involved in capillaries, venules, veins, and arteries. Magnetic resonance imaging systems can be divided into several parts and give very clear pictures of body tissue. PET and radionuclide scanning are non-invasive ways to see how cancers are spreading and how the body's metabolism is working. Neuroprospaper is a biomedical imaging and neuroscience tool that is as small as possible to avoid being invasive. Radiologists use Magnetic Resonance Imaging (MRI) to take pictures of the body's anatomy and diseases that are happening in the body. MRI is more flexible than CT scans and X-rays because it can take pictures of the body from any angle and depth. It is used in hospitals and clinics and is better than CT scans for staging and diagnosis. MRI can be used for a lot of different things, like neuroimaging, cardiovascular, musculoskeletal, angiography, liver and gastrointestinal, and more. Brain tumours can happen at any stage, and the symptoms depend on the type, size, and location of the tumour. Primary brain tumours start in the brain and can be either cancerous or not. Meningiomas and gliomas are two common types of brain tumours. They come from nerve cells, glands, brain cells, and the membranes that surround the brain. Other types of primary tumours are pituitary tumours, pineal gland cancers, ependymomas, CNS lymphomas, primary germ cells, Schwannomas, and craniopharyngiomas [8].

Secondary brain tumours start in the brain but can spread to other parts of the body, such as the lungs, breast, or kidneys, and then spread back to the brain. They can be cancerous, but they don't spread from one place to another. A physical exam and medical history are the first steps in finding out if someone has a brain tumour. Neurological tests, like a neurological exam, are done to check the patient's coordination, math skills, memory, and muscle strength. CT scans, MRI scans, skull x-rays, biopsies, and angiography are all tests that can be used to find and treat brain tumours. Finding out if someone has a brain tumour is very important for saving lives and lowering the risk of long-term disability. Brain specialists and neurologists do physical exams, tests, and look at nerve systems to find out if someone has a brain tumour. To check for seizures, doctors may also order PET scans, SPECT, and EEG tests. Segmentation of images is an important part of image processing. There are three main types of segmentation: manual, semi-automatic, and fully automatic. Automatic segmentation is difficult, but there are now semi-automatic ways to separate brain tumours from MR images. Semi-automatic segmentation is mostly done by software, which gives better results than manual segmentation. Artificial intelligence and prior knowledge are used in fully-automatic segmentation to figure out how to segment a tumour without any help from people. Computer-aided diagnosis (CAD) systems help doctors make sense of medical images like X-rays, ultrasounds, and MRIs. CAD is used to find brain tumours, lung cancer, breast cancer, coronary artery diseases, congenital heart defects, nuclear medicine, Alzheimer's disease, and diabetic retinopathy. CAD gives very accurate diagnoses by having expert endoscopists take EC pictures and use dye to stain them. Minimum Distance Classifier (MDC), Cascade Classifier (CC), Nearest Neighbour Rule (NNR), Naïve Bayesian classifier (NBC), Support Vector Machine (SVM), Artificial Neural Network (ANN), Radial Basis Function Network (RBF), and Principle Component Analysis (PCA) are some of the algorithms that can be used to get accurate segmentation. In conclusion, diagnosing brain tumours is very important for saving lives and lowering long-term disability [9].

LITERATURE SURVEY

This paper examines segmentation techniques for identifying brain tumours through clustering and morphological filtering. The emphasis is on techniques including potential field segmentation, enhanced tumour cut segmentation, statistical region fusion segmentation, Random Forests (RF), and Conditional Random Fields (CRF). The authors evaluate these methods against cutting-edge techniques to ascertain their superior quality [10]. We also talk about ways to process medical images, and the Brain Tumour Image Segmentation (BRATS) MRI benchmark database is used a lot. To avoid misclustered areas in medical images, the authors suggest using K means clustering and filtering along with morphological filtering. A deep feature fusion approach for breast cancer diagnosis is introduced, tackling issues related to limited datasets, prolonged computation time, and extensive image preprocessing requirements. The method employs convolutional neural networks (CNNs) in conjunction with established radiomic frameworks to extract low to mid-level features from three modalities. Greenspan et al. (2016) present an effective approach for deep learning, enhancing artificial neural networks by incorporating additional layers for higher levels of abstraction and improved data computation. Convolutional neural networks (CNNs) are demonstrated to be an effective instrument for obtaining mid-level and high-level abstractions. The application of medical image analysis is introduced into a domain where CNNs and other deep learning techniques are scrutinised to address challenges [11].

Choi et al. (2013) examined the efficacy of hyperspectral image fusion techniques utilising contour let, identifying three categories of contour let transforms: original contour let transform, non-subsampled contour let transform, and contour let transform. The last two transforms did a better job of keeping spectral information and improving spatial resolution. Sharma et al. (2013) illustrated efficient techniques for image diagnosis utilising CAD-based methodologies, including the ANPOVA method and the genetic algorithm-based feature solution. El-Dahshan et al. (2014) exhibited the efficient identification of cervical cancer through the Neuro Fuzzy Inference System Classifier, utilising Pap Smear Images for screening and diagnosis.

Baraiya and Modi (2016) investigated various methodologies for brain tumour extraction from MRI images, evaluating the precision of multiple segmentation techniques. Mendonça et al. (2014) addressed the complex issue of vascular segmentation in the retina by altering the parameters of filters during preprocessing and vessel enhancement. Praveen & Agrawal (2015) suggested a hybrid method for detecting brain tumours and categorising MRI images through the use of rapid bounding boxes. These studies give us useful information about how well hyper spectral image fusion methods, image diagnosis, and segmentation techniques work. These studies suggest hybrid approaches to make these methods more accurate and precise. This is especially important in medicine, where image segmentation is important for scheduling surgeries and making medical decisions [12].

The study examines hybrid methodologies for image segmentation, encompassing blood vessel segmentation in the retina for the detection of diabetic retinopathy. A multilayer perceptron neural network was employed for the recognition of retinal blood vessels, detecting characteristics such as haemorrhages and exudates. The study also concentrates on categorising each pixel in retinal images into vessel and non-vessel classifications [13]. Teramoto and Fujita (2013) examine the identification of lung nodules in chest CT images utilising a cylindrical nodule enhancement filter. The suggested method consists of lung region segmentation, preprocessing, nodule enhancement, further segmentation, and the reduction of false positives. The research indicated that a lung nodule was identified earlier and more efficiently than with alternative methods [14]. Li et al. (2016) suggested a cross-modality method to improve performance without using features that were made up or preprocessing. They put forward a new supervised way to change data from one modality to another using a wide and deep neural network. The network output was the label map for every pixel in a given image patch. It was better than other methods in terms of sensitivity, specificity, and accuracy. Magnetic Resonance Imaging (MRI) is the best choice for medical diagnosis systems (MDS) because it can accurately capture soft tissues inside the body and show finer details. MRI has benefits like being safe, giving three-dimensional images, and being able to see blood flow around organ vessels.

Using fuzzy C-means (FCM) and graph cuts, Wu et al. (2017) came up with a semiautomatic way to divide up liver tumours in CT volumes. The method was tried out on 15 CT volumes with lumps of different sizes in the liver. Menze et al. (2015) enhanced brain tumour images utilising the BRATS dataset. Havaei et al. (2017) put forward a completely automatic method for separating brain tumours in MR images that is based on deep neural networks and is specifically designed for glioblastomas [15]. Manocha et al. (2017) utilised fuzzy C-means clustering to automate tumour segmentation for the purpose of delineating tumour regions. A dataset of T2-weighted images of 15 patients was used to evaluate the work. To make it easier for users to use, the GUI was made with fuzzy C-means clustering to separate tumours [16]. Sharma and Mukherjee (2014) suggested image segmentation in MRI images by employing grey level co-occurrence for the selection of texture features. Medical resonance imaging (MRI) is a diagnostic technique for image segmentation that employs methods such as thresholding, clustering, and soft computing techniques. Abdel-Maksoud et al. (2015) suggested a clustering methodology employing K-means and Fuzzy C-means techniques to achieve minimal execution time and enhanced accuracy [17].

Patel and Doshi (2014) put forth a segmentation method utilising a clustering approach for tumour detection in brain MRI, advocating for MRI due to its reduced radiation exposure. We looked at different clustering methods to find the best one for efficient segmentation. Prastawa et al.

(2004) created an automatic way to divide brain tumours into parts, which made it possible to find oedema right away. This method used T2 MR image channels that weren't enhanced to make tissue segmentation better. The process included finding abnormal areas, figuring out the intensity properties of the tissue, and finding oedema in those areas. The technique was utilised on three datasets, depicting tumour morphology, spatial distribution, dimensions, image intensities, and enhancements [18]. Maji et al. (2013) proposed a systematic classification methodology for Additive Kernel SVMs, enhancing accuracy and execution speed compared to linear SVMs. This method has been used on many different datasets and has been the basis for many different ways to recognise objects and classify images [19]. Mustaqeem et al. (2012) concentrated on brain tumour segmentation, emphasising watershed and threshold segmentation to precisely identify and measure tumours. We got the images we needed by using MRI scans and median and high pass filters to get rid of noise [20]. Javed et al. (2014) suggested an image fusion method that uses local features and fuzzy logic for Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). The method integrated critical data from MRI and PET images, yielding superior performance relative to traditional techniques [21].

Dhanachandra et al. (2015) employed clustering techniques to segment images, utilising the k-means clustering algorithm and the subtractive clustering method. Arivazhagan et al. (2013) discovered innate recognition and categorisation of plant leaf infections through texture features. The study examines the application of multiple classifier systems in the detection and classification of plant diseases. The method consists of converting leaf images to HSI format and then extracting and analysing features like contrast, energy, local homogeneity, shade, and prominence. The research demonstrated that the suggested algorithms effectively identified and categorised plant diseases with enhanced accuracy [22]. Woźniak et al. (2014) evaluated various classifier systems via hybrid systems, concentrating on pattern classification through the aggregation of multiple classifier systems. The research underscored the significance of diversity and decision fusion methodologies in the development of hybrid classifier systems. Hybridisation can be accomplished by amalgamating raw data from diverse sources, combining raw data with proficient processes, and integrating prior expert knowledge and classification models through machine learning methodologies [23]. Jermyn et al. (2013) put forward multimodal methods for approximating optical constraints in near-infrared and conservative imaging techniques. But the technology needs a lot of software, a lot of power, and a lot of time, which makes the mesh quality for optical image rebuilding bad. To address these challenges, the study introduced automated digital imaging and communications in medicine image stack segmentation, along with an innovative one-click three-dimensional mesh generator optimised for multimodal NIR imaging.

Benaichouche et al. (2013) put forward a method for efficient segmentation that used the fuzzy C mean algorithm. This method improved the output in three steps: first, it classified pixels, then it added spatial information and mahalanobis, and finally, it reclassified pixels that had not been classified before. Sujji et al. (2013) elucidated the thresholding-based methodology for image segmentation, encompassing threshold-based segmentation, edge-based segmentation, region-based segmentation, clustering, and matching [24]. Liu et al. (2014) examined graph theoretical approaches for image segmentation, classifying them into distinct categories: minimal spanning tree-based methods, graph cut-based methods, graph cut-based methods (Markov random field models), and optimal path-based methods. The paper also talked about data mining methods like random sampling, hierarchical clustering, and cluster analysis [25]. Kumar et al. (2016) illustrated the significance of image processing in lung cancer diagnosis through various methodologies, including Gabor filters, watershed segmentation for image segmentation, and feature extraction utilising MATLAB. The watershed segmentation method worked better than other methods for finding lung cancer cells.

Ma, Shen et al. (2014) created a cutting-edge object-oriented method that used both pixel-based arrangement and segmentation to sort polar metric synthetic aperture radar (PolSAR) images. Subasi (2013) created a new PSO-SVM model for particle swarm optimisation (PSO) and SVM to make it easier to classify EMG signals. The experiment consisted of breaking EMG signals into frequency sub-bands with the Discrete Wavelet Transform (DWT) and taking away sets of statistical features to show how wavelet coefficients are supplied in the recommended way [26].

Verma et al. (2013) examined edge pattern and brain segmentation to accurately diagnose brain tumours, emphasising the necessity of medical image segmentation to address the complexities in identifying brain abnormalities. The study established segmentation and edge detection as the initial phase for brain tumour classification [27].

RESEARCH METHODOLOGY

Brain tumours are a serious health problem around the world, but it's getting easier to find them early in young people. These tumours can be either malignant or benign. Malignant tumours grow quickly, while benign tumours grow slowly. CT scans, MRIs, X-rays, SPECT, PET, and ultrasounds are all digital imaging methods that can be used to find problems early on. Machine learning (ML) ideas have been used to process and classify images of brain tumours. Malignant gliomas, or anaplastic astrocytomas, are thought to be curable with full surgical treatment. Radiotherapy, chemotherapy, or a combination of the two can be used to treat grade III and IV gliomas. Glioblastoma is the most aggressive type of astrocytoma; it grows quickly and is very dangerous [28].

There are two main stages of learning in machine learning: supervised learning and unsupervised learning. Supervised learning sets the training data and reacts to the output data, while unsupervised learning looks at the set and reduces the number of dimensions of the information. The learning algorithm is very important for figuring out how to find and diagnose the problem. The suggested system has three steps: pre-processing, clustering, segmentation, and classification. The first step is to get rid of noise and equalise the histogram using Distribution based Adaptive Median Filtering (DAMF), Neighbourhood Differential Edge Detection (NDED), clustering tumours, Intensity Variant Pattern Analysis (IVPA), and Weighted Machine Learning (WML) classification. The machine learning classifier gives the image a set of examples to use when deciding whether it is normal or not.

The text talks about different filters that can be used to reduce noise and make images look better. These include the crimson speckle removal filter, the laplacian of Gaussian filter, and the unsharp filter. These filters are helpful for images with a lot of blur at high frequencies and for sharpening edges in photography and printing. But they also have some drawbacks, like lowering additive noise, smoothing, and skull from the image [29].

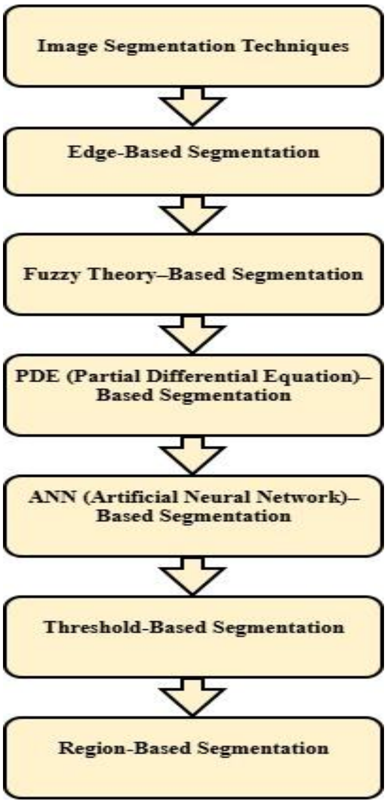

Fig.4 Image segmentation types

Adaptive median filtering is a more advanced version of standard median filtering that sorts pixels into noise by comparing each pixel in the image to the pixels next to it. The neighborhood's space can change, and the threshold for association is set. Impulse noise is when a pixel is different from most of its neighbours or is not physically connected to them. The median pixel value of the pixels in the area that passed the noise labelling test [30] is used to replace these noise pixels. The adaptive median filter is the main filter for the distribution-based adaptive median filter (DAMF), which is what the DAMF is based on. Preprocessing is very important in medical imaging because the original image has noise and artefacts that make the image look bad. To get rid of the skull and extra noise in the image, we use Distribution-based Adaptive Median Filtering (DAMF). This method works with the standard medical filtering method, which uses the Gaussian distribution function to do the filtering [31].

Images of brains are loaded in, and the right pseudocode is used to figure out the index of the image based on the lowest and highest pixel intensity values. We know the maximum area of components in the whole image, and we can guess how far off the maximum labelled matrix and normalised pixel value are from that. Clustering is an important part of unsupervised learning. Its goal is to organise data that doesn't have labels into groups. There are two kinds of clustering: clustering by distance and clustering by concept. Distance-based clustering sorts data into four groups based on how far apart they are, while conceptual clustering finds common entities from two or more entities. The purpose of clustering is to identify the intrinsic groupings within unlabelled data, to condense the data, and to categorise the characteristics of natural data types [32].

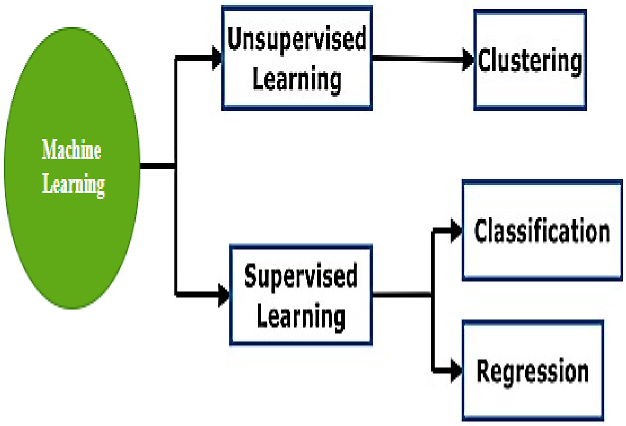

Fig.5 Machine Learning Types

Edge detection is a way to find sharp changes in how bright an image is, like when the scene gets clearer, the material changes, the surface lines up, or the depths get confused. It includes image processing, computer vision, pattern recognition, and image analysis. Edge detection properties can be either dependent on the viewpoint or not [33]. There are usually three types of edges: diagonal, vertical, and horizontal. Diagonal edges can be either vertical or horizontal. The operator of horizontal gradient finds vertical edges. When gradient values are normalised and shifted, horizontal edges make vertical edges in the picture, which makes it easier to find vertical gradients. Detecting edges makes an image sharper by making the areas around the edges clearer. Robinson Compass Masks, Prewitt Operators, Kirsch Compass Masks, Sobel Operators, and Laplacian Operators are all masks that can be used to find edges. There are two types of filters: smoothing filters and linear filters. Sharpening is the opposite of blurring, in which the edge content gets smaller while the rest of the image gets bigger. To make an image sharper, you need to find the edges and add them to the picture.

The NDED technique is used to group pixels that are affected by tumours in a skull-removed image into clusters based on an analysis of the difference in intensity and an estimation of the pattern. The algorithm starts with the pre-processed image Y and a (3x3) matrix, finds the mean value, and then projects the window over the matrix Tm. It is put into a cluster based on how different the pixels around it are. The intensity variation pattern analysis is used to split an image into smaller parts for further processing by separating pixels that are affected by tumours. The segmentation process is what makes the image processing system work. To find the tumours in the image, the maximum intensity is used to find the spot where they are, and the pattern of the clustered data is extracted and shown in a histogram to show the tumours' level in the image. The algorithm takes the clustered output image I c as input, sets up a 5x5 window, finds the difference between the centre and the neighbouring pixels at different angles, figures out the index of the difference matrix, extracts the pattern, and uses the histogram of the extracted pattern to figure out the feature vector F. In short, the NDED method uses intensity difference analysis and pattern estimation to group together pixels that are affected by tumours in images of skulls that have been removed. This method deals with problems like stability, scalability, efficiency, and robustness in pattern analysis. A histogram is a tool for designing data that shows the shape, relative frequency, and centre of the data. It helps you figure out the output requirements and target customers for all of your needs. People often mix up histograms and bar charts because they both have seven basic quality controls. It is used for continuous data and for images that are grouped together. Algorithm III – Intensity Variation Pattern Analysis (IVPA) is an algorithm that uses the ideas behind histograms to figure out the feature vector. It means counting the number of data points, setting the sample range, setting the number of class intervals, controlling the thickness of the interval class, and improving the database or table for each interval. Skull removal is a surgical procedure that entails excising a portion of the skull to reveal the brain. Using histogram computation and skull removal, image processing can accurately break this process down into parts. The algorithm uses IVPA methods to find patterns in the histogram and guess the feature vector. Weighted machine learning classification is a method for figuring out what class a set of data points, also called labels or targets, belongs to. It uses binary classifiers to get close to mapping functions, input variables, and output variables. Classification is useful for medical diagnosis, target marketing, and getting credit. There are two kinds of learners: those who are lazy and those who are easy. Lazy learners gather input data and wait for output data to work, while easy learners have classification models based on the training set they get from classifiers before they get it.

Supervised machine learning algorithms learn how to sort new observations and input data into different groups. There are two main types of these algorithms: statistical and structural. They can be bi-class or multi-class. Some of the classified machine learning algorithms are linear classifiers (like Naïve Bayes and logistic regression), decision trees, artificial neural networks, boosted trees, k-nearest neighbours, random forest, and support vector machines [34]. Decision trees are used to make regression or classification models that follow a complete and mutually exclusive set of rules. They can process both numerical and categorical data, but they can become overfit if there are too many branches. Naive Bayes classifiers are basic probabilistic classifiers that use Bayes' theorem and make strong independence assumptions. Random forests are quick, don't overfit, and work well with data that has a lot of dimensions. Artificial neural networks have weights and are linked to input and output units. They can show real-time applications and give better results when you use input/output values. K-nearest neighbours are lazy learning algorithms that keep training data in n-dimensional space.

In machine learning, classification models have performance and cost functions like accuracy, sensitivity or recall, specificity, precision, and the ROC curve. Classification-based WML methods are used to tell the difference between normal and abnormal tumours. The algorithm takes in a feature vector F, a training feature F train, and a label Lb. We figure out the normalised value of the feature vector and then give the weight vector W x and W y based on the angles of θ x and θ y. The location is found by looking at the highest points of H 1 and H 2 and guessing the x and y coordinates. We find the Root Mean Square (RMS) value for the weight and then update the coordinates, weight matrix, and angle. The final class results are determined by the index of the lowest RMS (Root Mean Square) value. A brain tumour segmentation technique employing a one-class Support Vector Machine (SVM) has been introduced, capable of learning the nonlinear distribution of image data without prior knowledge. Researchers utilised numerous MRI modalities to generate voxel-wise intensity-based feature vectors, subsequently classified using SVM. We suggest and use Relevance Vector Machine (RVM) classification methods on brain images. The main goal is to get great results for MRI brain cancer classification using RVM. The benefits of these techniques encompass enhanced classification precision, adequate interpretability, and diminished complexity and time expenditure [35].

Analysis Report

The study concentrates on the detection of brain tumours, which holds significant promise in clinical medicine. The primary obstacles in automatic tumour detection arise from the heterogeneity of brain tumours, their deformation, and the deterioration of healthy brain sagittal symmetry. Magnetic Resonance Imaging (MRI) is a cutting-edge way to take pictures of the body that is used to treat brain tumours. Image segmentation is very important for getting the right numbers for certain areas. However, there have been problems like over-segmentation, more complexity, and taking up too much time [36].

The goal of this project is to create a good way to segment and classify MRI brain tumours. The proposed system preprocesses images by removing extra noise from the given MRI using techniques like Distribution based Adaptive Median Filtering (DAMF), Neighbourhood Differential Edge Detection (NDED), Intensity Variation Pattern Analysis (IVPA), and Weighted Machine Learning (WML). Real patient data from the 2013 brain tumour segmentation challenge (BRATS2013) was used for the experiments. There were three parts to the dataset: training, test, and leaderboard. The model goes through about 2.2 million examples of healthy patches and 3.2 million examples of tumorous patches. Some of the performance measures used to evaluate results are 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 is the ratio of true negatives to the sum of true negatives and false positives. It tells you how many negatives were correctly identified as such. Accuracy is the difference between a measured value and a standard or known value. It can also be thought of as a weighted arithmetic mean of Precision and Inverse Precision, or a weighted arithmetic mean of Recall and Inverse Recall. Precision is the percentage of retrieved instances that are relevant to the query. It is calculated by dividing the number of true positives by the total number of true positives and false positives. Recall, also called sensitivity, is the percentage of relevant instances that are found. It gives the most accurate results for detection. The ratio of true positives to the sum of true positives and false negatives is how it is figured out [37].

The Jaccard Coefficient assesses asymmetric information on binary variables by evaluating matching items where the negative value is superfluous, rendering the non-existence value irrelevant. The Dice Coefficient uses the precision p and recall r statistics to measure accuracy, while the Kappa Coefficient uses the Kappa Coefficient to measure agreement between rates for qualitative items. To sum up, information retrieval algorithms need to have specificity, accuracy, precision, recall, the Jaccard coefficient, the Dice coefficient, and the Kappa coefficient. All of these things are very important for figuring out how accurate and efficient the segmentation process is. We look at the performance of the proposed Intensity Variation Pattern Analysis using Weighted Machine Learning (IVPA-WML) approach and compare it to other methods that are already in use. The IVPA-WML is compared to two other methods, the Support Vector Machine (SVM) and the Relevant Vector Machine (RVM), based on certain parameters. SVM is a type of classifier that uses a separating hyper-plane, while RVM is a machine learning method that uses Bayesian inference to find simple solutions for regression and probabilistic classification. The IVPA-WML technique is much more sensitive than the SVM and RVM techniques that are already out there. Its sensitivity and specificity both go up by 13.63%. The proposed IVPA-WML technique is more accurate than the SVM and RVM techniques that are already in use. The SVM method is 87.09% accurate, and the RVM method is 88.70% accurate in terms of sensitivity. The IVPA-WML method is 7.56% more accurate than the RVM method. The comparison shows that the proposed IVPA-WML technique is more accurate than the SVM and RVM techniques that are already in use. This means that the suggested IVPA-WML method can be used to process images in a way that is both more effective and faster. The research assesses the efficacy of image segmentation through precision and recall metrics. The proposed IVPA-WML technique has a higher recall rate of 92.95 than the existing SVM and RVM techniques. This is a comparison of the precision rates of the existing SVM, RVM, and IVPA-WML techniques. The proposed IVPA-WML technique has a recall rate that is 13.63% higher than the existing SVM and RVM techniques. To see how similar the segmented image is to the original image, we use similarity coefficients like Jaccard, Dice, and Kappa. The study finds that the suggested IVPA-WML method has a higher Jaccard coefficient value than the current SVM and RVM methods. The research evaluates the efficacy of current SVM, RVM, and IVPA-WML methodologies. The proposed IVPA-WML technique has a Dice coefficient value that is 13.63% higher than the existing SVM and RVM techniques. The Kappa coefficient of the proposed IVPA-WML method is also higher than that of the SVM and RVM methods. We also look at the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). The suggested IVPA-WML method has a best False Rejection Ratio of 4.0323 for Class 1 and 0 for Class 2. This shows that it works better than other methods. The Genuine Acceptance Rate (GAR) is the sum of the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). For Class 1, the GAR is 95.96, and for Class 2, it is 100. This shows that the system works. The ROC plot of the true positive rate against the false positive rate for all possible systems shows how well the tumour segmentation and classification system works overall. The proposed IVPA-WML technique has a higher ROC than the SVM and RVM that are already in use. The proposed IVPA-WML technique provides a superior and more efficient approach for tumour segmentation and classification.

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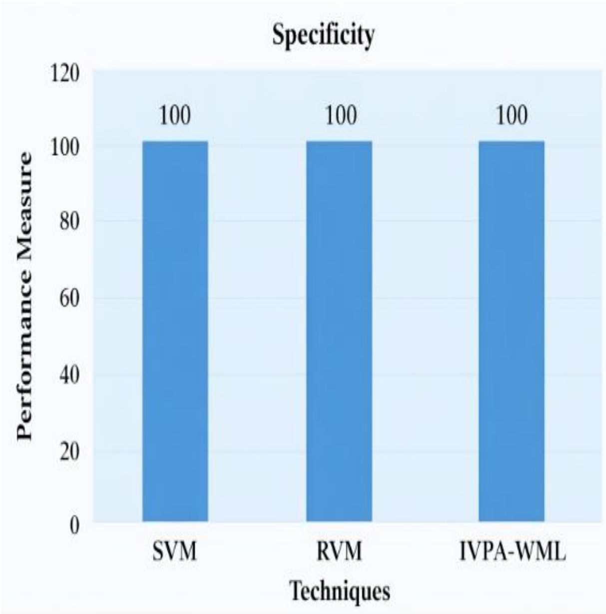

Fig.9 Analysis of Specificity Measure

This research compares current and proposed classification methods by using Dice, Sensitivity, and Specificity as metrics. There are different ways to use Convolutional Neural Networks (CNN) for classification. The results show that the proposed Intensity Variant Pattern Analysis-Weighted Machine Learning (IVPA-WML) method has a better Dice value than all the other methods that are currently available. When compared to other methods, it also has a high Sensitivity value. The proposed IVPA-WML has a higher Specificity value than any other method.

We also look at other things, like the latitude offset, the geocentric translation file, the longitude offset, the Easting offset, the Vertical offset file, and the Bin grid origin. The results show that the IVPA-WML technique works much better than other techniques, which means that it is better by nature. The results show that the new method works better than the old ones. We use similarity coefficients like Jaccard, Dice, and Kappa to compare the proposed method to other methods. The proposed system is also tested on the False Acceptance Ratio (FAR), the False Rejection Ratio (FRR), and the Genuine Acceptance Ratio (GAR). The findings indicate that the suggested IVPA-WML method is effective for detecting brain tumours in MRI scans.

CONCLUSION

This study introduces an effective segmentation and classification system for MRI brain tumour detection, emphasising the attainment of efficient detection in comparison to manual techniques. The system uses different image processing methods, such as Intensity Variation Pattern Analysis-Weighted Machine Learning (IVPA-WML), to divide tumour areas based on their texture and intensity patterns. The BRATS2013 dataset is used by the proposed system, which has 30 patients in the training set and 25 patients in the testing set. The system also does a good job of separating the skull area so that results aren't misclassified.

We use a number of performance measures to test how well the proposed system works. These include sensitivity, specificity, accuracy, precision, recall, similarity coefficients, False Acceptance Ratio (FAR), False Rejection Ratio (FRR), and Genuine Acceptance Ratio (GAR). The IVPA-WML method is more accurate and precise than other methods. The proposed structure focused machine learning algorithm is used to find brain tumours with a high level of accuracy and the least amount of time. Future research can improve the system by using this segmentation method to predict different levels of brain tumour abnormalities, reduce the number of features, and use deep learning methods for intense training. There are also suggested feature selection techniques and algorithms for finding tumour tissue..

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