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A Comprehensive Study on Brain Tumor and Stroke Detection from MRI Images Using Machine Learning Techniques

Rupak Kumar
Ph.D. Research Scholar,
Department of Computer Science,
C. S. J. M. University, Kanpur.
rupaknifft@gmail.com

Dr. Rashi Agarwal
Faculty of Computer Science,
Department of Computer Science,
C. S. J. M. University, Kanpur.

Dr. Renu Jain
Head of the Department,
Department of Computer Science,
C. S. J. M. University, Kanpur

Abstract

The human brain produces every action, thought, remembrance, sense, and understanding of the world. Structural changes in the brain cause brain abnormalities, such as tumors and strokes, which are the most commonly occurring neurological disorders. Detecting and analyzing these abnormalities is a challenging task for neuroradiologists. Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are the most common and effective modalities used by physicians for detecting neurological disorders. Computer Aided Diagnosis (CAD) is considered the most significant tool in detecting brain abnormalities. However, existing CAD approaches have some drawbacks, such as lower accuracy, efficiency, robustness, reliability, computational complexity, and disability to detect the severity level of the abnormality. To overcome these problems, a few novel approaches in CAD systems are proposed in the current research for relatively better diagnosis and analysis of MRI brain tumor and stroke. The proposed CAD process includes five phases: image fusion, image segmentation, feature extraction, feature selection, and image classification. The brain MRI sequences chosen are taken from BRATS 2013 and ISLES iv 2015 databases. The proposed techniques include Gradient based Discrete Wavelet Transform (GDWT), Intensity Factorized Tresholding (IFT), and Maximum A Posteriori (MAP) based Firefly Optimization Algorithm (MFFA). The Hybridized Support Vector based Forest Classifier (HSVFC) is proposed for the classification of MRI brain tumor and stroke.

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

Introduction

Computer Aided Diagnosis (CAD) is a system that assists radiologists in diagnosing various diseases, such as colon cancer, breast cancer, bronchial carcinoma, Alzheimer's disease, diabetic retinopathy, congenital heart defects, and coronary heart disease. CAD aims to identify abnormal signs early, which human professionals often fail to find, reducing false predictions [1]. It is widely used in medical applications such as genetic engineering, personalized medical transplants, artificial joint fixation, and robotic surgeries. CAD systems consist of four main modules: image pre-processing, segmentation of desired region of interest (ROI), extraction and selection of features, and classification of the selected ROI. The system involves acquiring brain images from MRI scans for disease prediction, preprocessing to improve precision and image quality, segmentation to understand and analyze affected parts, feature extraction to fetch meaningful information, feature selection to make the data accessible, and classification algorithm to categorize abnormal input [3]. The CAD system's

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outcome is compared with the expert neuroradiologist's opinion to avoid misprediction of disease identification [4].

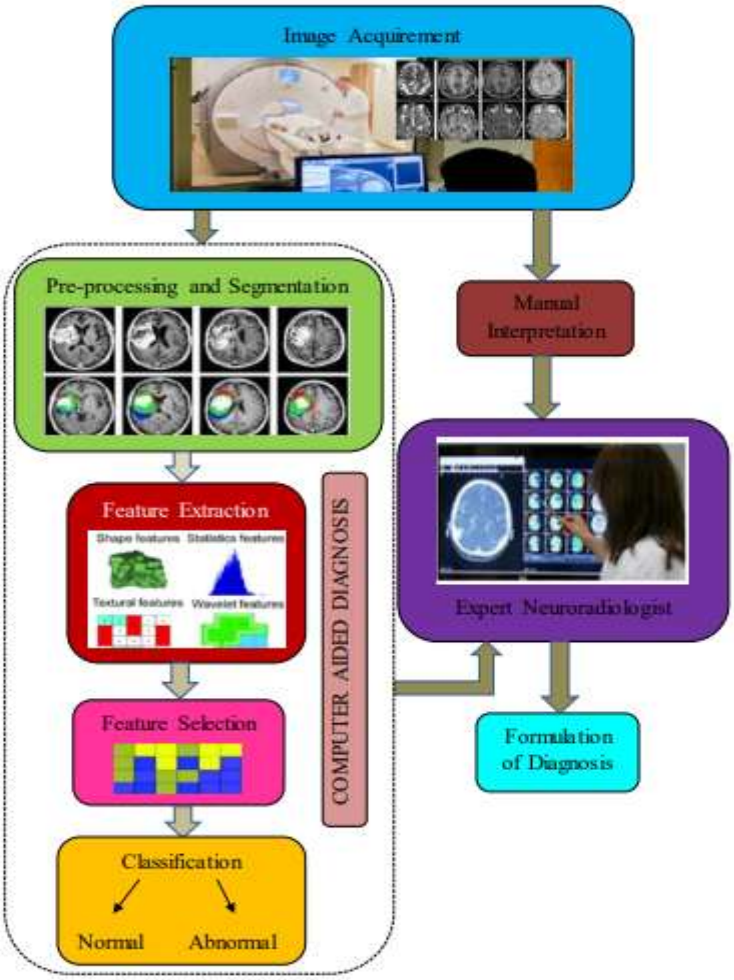

Fig.-1 Flow diagram for pathology detection using CAD System

The CAD system is an essential tool in detecting brain abnormalities due to its high accuracy, robustness, reliability, and advanced features. It is used for detecting brain abnormalities like trauma, intracranial pressure, vascular conditions, autoimmune conditions, infections, seizures, and neurodegenerative disorders [5].

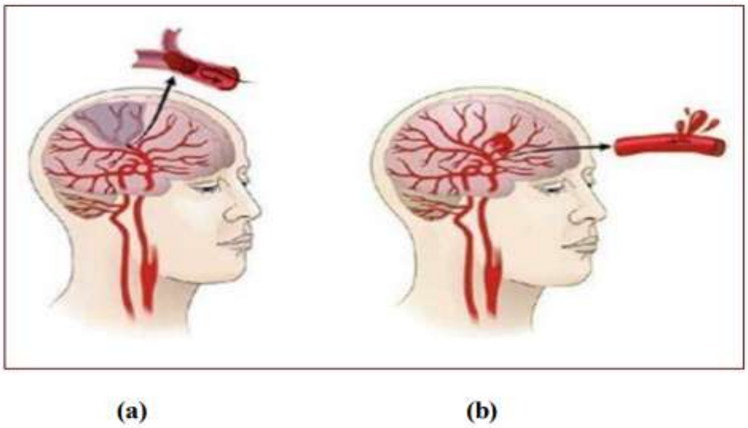

Fig.2 (a) Ischemic and (b) Hemorrhagic strokes

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Infections in the brain include meningitis, encephalitis, and brain abscess, while recurrent seizures are characterized by epilepsy. Trauma is associated with traumatic brain injury and intracerebral disorders caused by confusion and unconsciousness. Increased intracranial pressure leads to brain tumors, glioblastoma, hydrocephalus, normal pressure hydrocephalus, and pseudo tumor cerebri [6].

Vascular brain deformities include brain aneurysm, stroke, ischemic stroke, hemorrhagic stroke, Transient Ischemic Attack (TIA), cerebrovascular accident, subdural hematoma, epidural hematoma, cerebral edema, and intracerebral haemorrhage [7-10]. Autoimmunity irregularities include vasculitis and Multiple Sclerosis (MS). Neurodegeneration is found in Parkinson's disease, huntington's disease, pick's disease (fronto-temporal dementia), alzheimer's disease, dementia, and Amyotrophic Lateral Sclerosis (ALS).

Fig.3 Representation of brain tumor

The human brain controls all activities of the body and is protected by a skull. Brain abnormalities include psychiatric disorders, aging, and neurodegenerative disorders. Brain stroke is defined as a brain attack that occurs when blood vessels undergo bleed or rupture, or if there is any obstruction in the blood vessel that causes a shortage of oxygen level. There are two main categories of stroke: ischemic and hemorrhagic stroke. Diagnosis of stroke is possible through physical examination, lab and radiological investigation using CT scan, cerebral angiography, carotid ultrasound, MRI, and Magnetic Resonance Angiography (MRA). Stroke can be cured by medication and surgical treatment [11-15].

Brain tumors are abnormal cells growing in and around the brain, affecting people of any age. The World Health Organization classifies brain tumors based on their origin and behavior, with various types including benign, malignant, primary, and secondary. The exact cause of brain tumors is often unknown, and risk factors include ionizing radiations, family history, age, alcohol use, cellular phone use, chemical agents, electromagnetic fields, infections, tuberous sclerosis complex, Turcot syndrome, Li-fraumeni syndrome, and occupational exposures [16-20].

Tumors are treated with surgery, radiotherapy, chemotherapy, brachytherapy, and gamma-knife. Radiological diagnosis involves CT scans, Positron Emission Tomography (PET), MRI scans, Single Photon Emission CT (SPECT), Magnetic Resonance Spectroscopy (MRS), and functional MRI. MRI scans are commonly used for brain tumor and stroke detection due to

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their enhanced gadolinium and better outcomes than CT scans. Magnetic resonance imaging (MRI) is a non-invasive imaging technique that produces three-dimensional anatomical images without producing radiation. It is used to detect the brain's structure and detect activated areas, providing an innovative standard for measuring neurology status and risk. MRI sequences include T1-w, T1-c, T2-w, FLAIR, and DWI. FLAIR images show fluids as dark while lesions appear bright, while DWI images are more sensitive to water molecules' motion [21].

Literature Survey

This literature survey reviews various research on MRI brain tumor and stroke detection, CAD systems, image fusion, segmentation, feature extraction, selection, and image classification methodologies. CAD systems help doctors process medical images to find abnormalities in the human body. Some studies have applied computer-dependent recognizing methodologies, Content-Based Image Retrieval (CBIR), and autoencoding phenomenon to recognize even the smallest or early symptoms caused by Alzheimer's ailments. However, the maximum use of capsNet makes computation and implementation complex [22-25].

Various studies on CAD are classified into different types, including mammograms and brain-related disorders. The future scope and prospects of CAD are discussed, with data-driven techniques considered an optimal approach. Implementing a suitable system and algorithm requires normalizing test datasets and evaluation techniques [26].

A new devised CAD system is proposed for brain tumor detection and classification using K-means clustering, Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Support Vector Machine (SVM). The system classifies brain tumor images into abnormal and normal images, then categorizes them into noncancerous and cancerous. However, the large processing time limits its performance [27].

Several studies have proposed CAD systems for diagnosing brain ailments in MRI images, such as vascular dementia, Alzheimer's disease, multiple sclerosis, asymptomatic unruptured aneurysms, and brain glioma. These systems can be upgraded by improving diagnostic abilities and utilizing synergistic mainframes and high capabilities via information analysis with medical images [28].

Medical image fusion techniques combine information from different modalities for better disease diagnosis. Some methods include the two-dimensional Hilbert transform and Intensity Hue Saturation (IHS) method, which has minimal discrepancy and enhanced average gradient values. Discrete Cosine Transform (DCT) with saturation weighting and joint trilateral filter has been developed to improve quality but lacks an evolutionary algorithm for better spatial frequency enhancement. DWT is used for fusing brain images like CT and MRI in the frequency domain, preserving edge texture details but causing complications in image segmentation and classification [29].

Various state-of-the-art algorithms for image fusion have been reviewed, including wavelet transform, knowledge-based method, morphological techniques, neural networks, fuzzy logic scheme, IHS, PCA, and SVM. The success rate of stroke detection is low using CT images alone, so DWT is used to detect ischemic stroke accurately. Various imaging modalities like ultrasound, PET, MRI, and SPECT have been detailed, along

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with challenges such as resolution alteration, image noise, inter-image changeability, lack of adequate quantity of images per modality, enlarged computational intricacy, enhanced image space, and phase resolution [30].

Sanjay et al. (2017) developed a DWT-type2 fuzzy method for fusing CT and MRI images, splitting source images into sub-bands to enhance noticeable features. However, this study does not validate the performance of the DWT type2 fuzzy method.

Bhatnagar et al. (2013) introduced a unique framework for fusion of multimodal medical images based on the Non-Subsampled Contourlet Transform (NSCT), focusing on detecting brain tumors by fusing input images with better efficiency.

Qiu et al. (2019) proposed the fusion of multi-focus images using guided filter and median filter, achieving high computational efficiency and robustness to noises. Madanala and Rani (2016) explained the fusion of CT and MR images by combining DWT and NSCT methods, using PCA and maximum fusion rule. Ramlal et al. (2018) proposed the fusion of brain CT and MRI images based on Stationary Wavelet Transform (SWT), but the performance validation was limited to SWT rules. Li et al. (2018) addressed spatial difficulty in multi-modal image fusion using the Structure Aware Image Fusion (SAIF) method, which removes salient structures from various modal images and filters them using Iterative Joint Filter (IJF). Deepa and Sumithra (2017) analyzed various methods of fusion for brain abnormality detection, finding PCA yielding good outcomes for CT and MRI fusion, while DWT performs well for MRI-T1w and MRI-T2w fusion. Medical image segmentation techniques include Menze et al.'s generative model using atlas-based Gaussian mixtures and EM method for brain abrasion segmentation of stroke and tumor images, Shah and Chauhan's hybrid approach using Gaussian Mixture Model (GMM) based Expectation Maximization (EM) with Hidden Markov Random Field (HMRF), Liu et al.'s patch-based augmentation of EM after premature birth, and Isa et al.'s K-means clustering and Otsu-based thresholding for segmenting brain MRI-T2w images [31].

Chen et al. (2017) introduced a new framework for stroke lesions segmentation in diffusion-weighted MRI images, incorporating two convolutional neural networks: Multiscale Convolutional Label Evaluation Net (MUSCLE Net) and Ensemble of two DeconvNets (EDD Net). However, this approach has a drawback of reduced system efficiency and segmentation of desired regions in multiple scale images. Oo and Khaing (2014) introduced a method for tumor detection using the morphological operation of erosion algorithm and watershed segmentation. Dhage et al. (2015) used watershed segmentation to divide normal and abnormal tissue from MR images, but there is no clarity in localizing tumor areas. Deepa and Sumithra (2016b) developed a hybrid approach for MRI images to detect brain pathology using modified FCM clustering and level set method. Abdel-Maksoud et al. (2015) proposed an effective image segmentation method by combining the K-means clustering method and the Fuzzy C-means algorithm, followed by level set and thresholding method for exact recognition of brain tumors. Havaei et al. (2016) reviewed deep learning approaches for diagnosing brain pathologies, including Convolutional Neural Network (CNN) methods in medical imaging applications. Feng et al. (2015) proposed a segmentation algorithm for multispectral images, while Reboucas et al. (2017) recommended an innovative approach for CT stroke image segmentation. Suganya and Krishnaveni (2016) analyzed various brain segmentation techniques for ADHD. Lemieux et al. (1999) recommended fast and accurate automated segmentation of brain images from T1-w MRI using thresholding and morphological operations [32].

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The text discusses various methods for segmenting brain images, including histogram analysis, image fusion, instinctive segmentation, small patch-based representation with label fusion, attenuation residual U-Net, ensemble approaches, amalgam techniques, and hybrid methodologies. These techniques aim to increase diagnostic accuracy by extracting features such as local neighborhood, intensity, and wavelet texture from preprocessed images.

Feature extraction and selection techniques are also discussed, with methods like Usman and Rajpoot's brain tumor segmentation and classification approach, Chaddad's automated technique for feature extraction in brain tumor MR images, and Gumaste and Bairagi's hybrid feature extraction technique.

Deep et al. introduced the Local Directional Ternary Quantized Extrema Pattern (LDTQEP), which uses ternary patterns from a horizontal-vertical-diagonal-antidiagonal (HDVA) of the directional local extrema values for encoding additional spatial data. However, this method fails to include features in the remaining directions, limiting further processing of images.

Huda et al. addressed the issue of imbalanced medical data for brain tumor diagnoses by employing the hybrid feature selection technique. This technique reduces the effect of an imbalanced dataset by selecting features that are present in all directions.

In conclusion, various techniques have been developed to improve the efficiency and accuracy of brain tumor segmentation and detection in MRI images. However, limitations such as computational time complexity, lack of feature selection, and the need for more accurate and efficient methods remain.

The text discusses various classification techniques for MRI brain images, including ensemble-based approaches, hybrid feature selection, and image classification. Ensemble-based approaches are used to select the best features from images, while hybrid feature selection offers a simplified diagnostic rule set for detecting tumors from imbalanced datasets. Jothi (2016) proposes a Tolerance Rough Set Firefly based Quick Reduct for brain MRI images, which uses shape, texture, and intensity-based features to select significant features of brain tumors.

Classification techniques for MRI brain images include KNN algorithm, Linear Discriminant Analysis (LDA), Bee Colony Optimization (BCO), Feed-Forward Neural Network (FFNN), SVM classifier, CNN, Gabor filter with SVM, rule-based classification, and random forest classifier. These techniques have been tested and evaluated for their accuracy, performance, and accuracy in different datasets and regions.

Automated classification of brain tumors for MRS spectra is suggested by Tate et al. (1998), but the results are limited to T2-w MRI images alone and fail for MRI images with different resolutions. Subramaniam and Radhakrishnan (2016) emphasize the use of Bee Colony Optimization (BCO) with neural network hybridization, while Karrat et al. (2010) introduce an amalgam method for classifying brain tissues in MRI using SVM classifier.

CNN is used for brain tumor classification in MRI images, but its performance validation is restricted to T1-c MRI alone. Gilanie et al. (2018) develop a technique for classifying MRI brain slices into normal and abnormal images using a Gabor filter with SVM.

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Saad et al. (2017) present a technique for automatic diagnosis and detection of stroke in DWI images using rule-based classification. However, the method fails to provide distinctions among tumor core edema, active tumor, and necrosis. The detection of brain tumors and strokes is crucial for efficient treatment, but MRI images often lack quantification of tumor areas, leading to challenges in detecting small calcifications and evaluating blood brain barrier presence. Various approaches have been used for diagnosis, but some have limitations such as computational time complexity, difficulty in determining abnormality severity, and low accuracy rates. Challenges in segmenting tumor and stroke lesions include missing edge information, blurring effects, resolution alternation, and lack of spatial data.

The research aims to propose a novel algorithm for CAD systems that includes a fusion algorithm for better identification and clarification of MRI results, a suitable segmentation algorithm, enhanced feature extraction techniques, suitable feature selection methods, and an appropriate classification algorithm for detecting brain tumors and strokes in MRI images.

The input dataset consists of stroke and tumor-affected MRI brain images, with pathology detection using a KNN algorithm. The proposed Gradient based Discrete Wavelet Transform (GDWT) is used for image fusion, and the segmentation of the fused image is done using the Intensity Factorized Threshold (IFT) method for segmentation. The proposed algorithm aims to improve classification accuracy and reduce complexity in real-time applications.

Research Methodology

Image segmentation is the process of dividing an image into distinct areas that each contain pixels with the same properties. By enumerating a few key elements like closeness, resemblance, and good continuation, this can also be seen as a kind of grouping that incorporates perceptual combination and organization in vision (Pham et al. 2018).

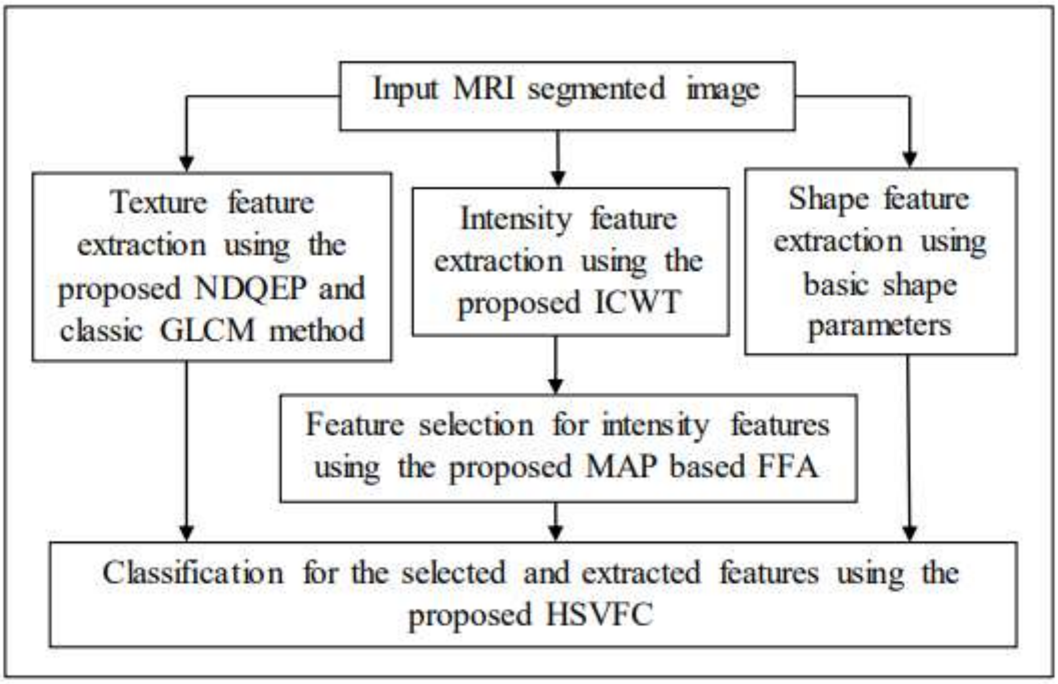

Fig.4 Overall flow of brain MRI classification

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Thousands of algorithms have been created so far for the segmentation process, and each one differs slightly from the others. The various categories of image segmentation algorithms are as follows: Normalized cuts, split and merge, clustering, region growing, and threshold are examples of region-based algorithms (Li et al. 2017a). Robert operator, prewitt operator, and sobel operator are examples of edge/boundary based algorithms (Li et al. 2017b). Soft computing techniques include fuzzy logic, neural networks, and genetic algorithms. The process of image segmentation is crucial for many biomedical imaging applications, pathology location diagnosis, and the study of functional structures.

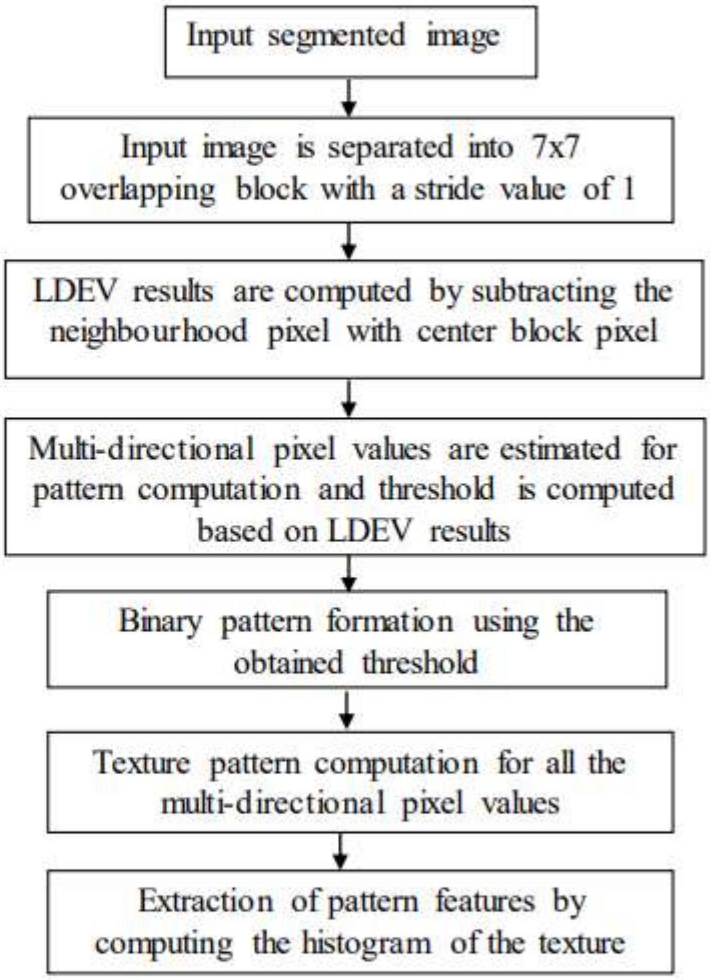

Fig.5 Flow of the proposed NDQEP technique

Brain image segmentation is regarded as a difficult problem that has drawn a lot of attention. Medical images are linked to issues such as data archiving, image fusion of different modalities, overly disparate spatial and temporal scales, and the uncertainties involved in the display and extraction of quantitative data. Segmentation, which involves separating various tissues from one another, is an effective way to address these. Representing the segmented regions into meaningful, more dependable, and computationally tractable areas of the image is the aim of medical image segmentation (Milletari et al. 2016). Furthermore, in certain instances, the regions may consist of collections of border pixels that can be arranged into structures in pictures of 3D industrial objects, such as line segments and circular arc segments (Smistad et al. 2015). Segmentation is frequently used in brain MRI analysis to visualize and quantify changes in the brain, plan surgeries, examine the brain's anatomical structure, and

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identify pathological areas (Deepa and Sumithra 2019). Brain segmentation is used to separate the white matter, grey matter, and cerebrospinal fluid. It is specifically used to extract the tumor region from MRI images. Furthermore, the development of pathological brain structures and the general modeling of pathological brains benefit from precise stroke and tumor diagnosis (Sazzad et al. 2019). Since the affected and non-affected regions of an MRI vary in intensity, the current study presents the use of the IFT technique for image segmentation in order to identify both MRI brain tumors and strokes.

Analysis Report

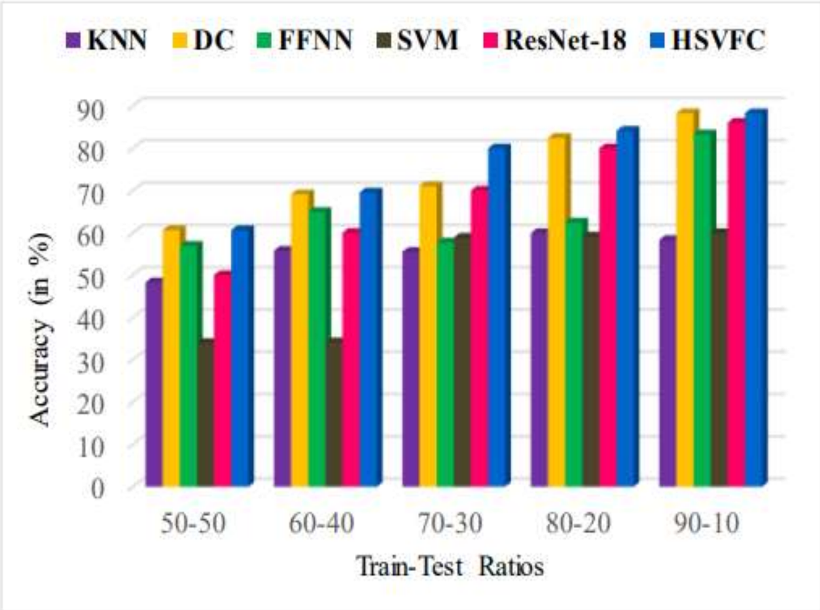

Fig.6 Accuracy measure of various classifiers for MRI brain tumor images with different train-test ratios

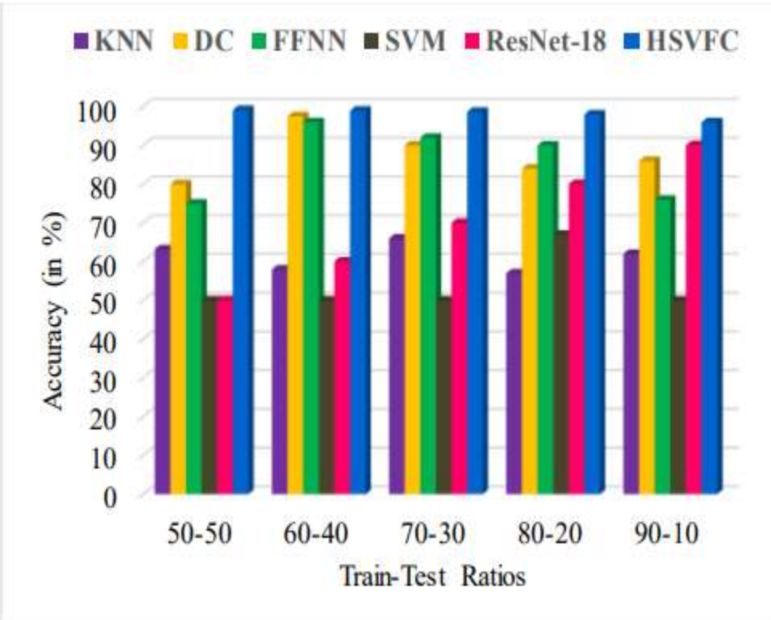

Fig.7 Accuracy measure of various classifiers for MRI brain stroke images with different train-test ratios

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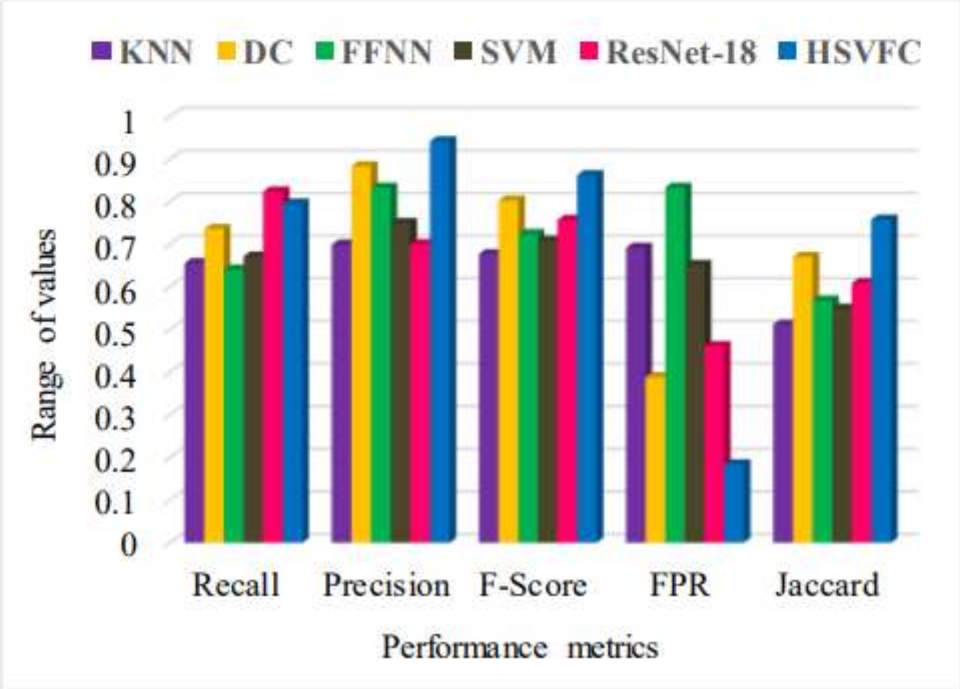

Fig.8 Result analysis of various classifiers for MRI brain high grade tumor images with 70-30 as the train-test ratio

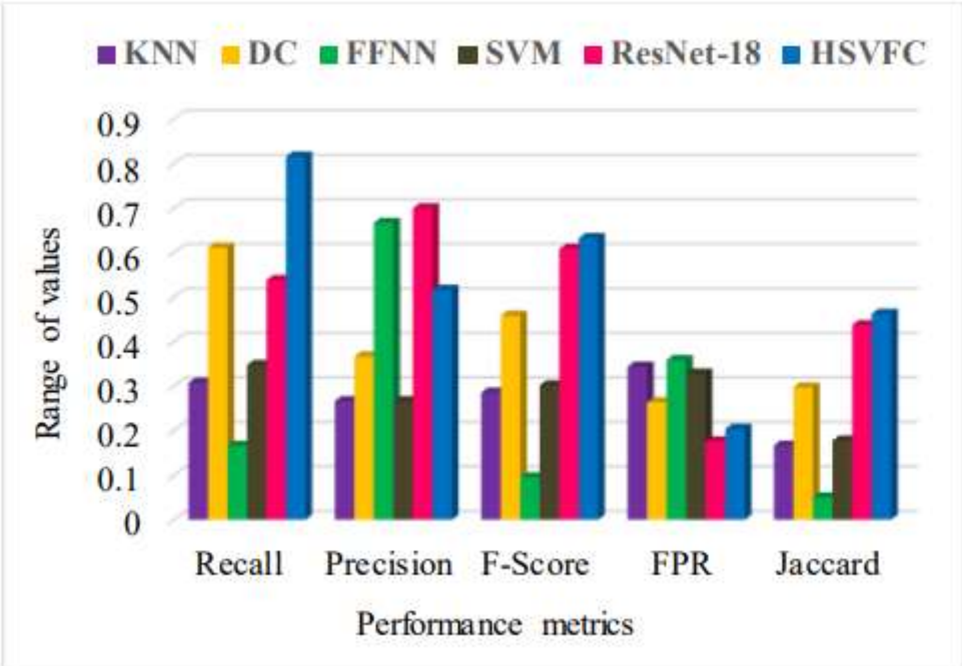

Fig.9 Result analysis of various classifiers for MRI brain low grade tumor images with 70-30 as the train-test ratio

In order to differentiate between stroke and tumor in brain MRIs, this paper presents a hybridized classification method that combines SVM and RF techniques. Furthermore, MFFA is projected as a feature selection technique to enhance the classification process, and NDQEP and ICWT are suggested for feature extraction. MRI brain tumor images are identified and categorized as low grade and high grade tumors using the suggested HSVFC method. Similar to this, acute and sub-acute strokes are identified and categorized from MRI brain stroke images. Three distinct regions—edema, necrotic tumor core, and non-enhancing tumor core region—are recognized and highlighted with various colors in tumor detection.

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According to the experimental analysis, the average accuracy of HSVFC for classifying MRI brain tumors is higher than that of SVM by 43.42%, FFNN by 16.13%, DC by 2.90%, ResNet-18 by 10.01%, and KNN by 31.68%. In a similar vein, HSVFC's average accuracy in classifying MRI brain strokes is higher than that of SVM by 53.40%, FFNN by 13.45%, DC by 11.49%, ResNet-18 by 33.42%, and KNN by 46.33%. Regarding the classification of MRI brain tumors, the best F-score of 0.91 and the lowest FPR of 0.06 are obtained for the suggested HSVFC. In the case of MRI brain stroke classification, HSVFC achieves an FPR of 0 and the best F-score of 0.99.

Conclusion

The human brain’s complexity makes the diagnosis of structural abnormalities like tumors and strokes a challenging yet critical task. While MRI and CT imaging have become essential tools for detecting neurological disorders, traditional Computer Aided Diagnosis (CAD) systems often fall short in terms of accuracy, computational efficiency, and the ability to reliably classify and assess the severity of abnormalities. These limitations necessitate the development of more robust and intelligent diagnostic frameworks. This research addresses those gaps by proposing an enhanced CAD system that integrates advanced image processing and machine learning techniques. The five-phase diagnostic pipeline—comprising image fusion, segmentation, feature extraction, selection, and classification—offers a comprehensive and structured approach to brain abnormality detection. The use of Gradient-based Discrete Wavelet Transform (GDWT) and Intensity Factorized Thresholding (IFT) ensures high-quality feature representation, while the Maximum A Posteriori-based Firefly Optimization Algorithm (MFFA) improves feature selection efficiency. Furthermore, the proposed Hybridized Support Vector-based Forest Classifier (HSVFC) significantly enhances classification performance by combining the strengths of both Support Vector Machines and Random Forest classifiers. Experiments conducted on BRATS 2013 and ISLES iv 2015 datasets demonstrate the effectiveness of the proposed techniques in accurately detecting and differentiating brain tumors and strokes. The improvements in diagnostic precision, reliability, and computational feasibility highlight the system’s potential for real-time clinical deployment. Overall, this research contributes meaningfully to the evolution of CAD systems in neuroimaging, paving the way for earlier detection, better prognosis, and improved patient outcomes in the context of brain abnormalities.

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