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Early Uncovering of Brain Tumour using Hybrid Machine Learning Techniques

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Abstract:

The human brain is an advanced structure that includes the brain, spinal fluid, and cerebro-spinal fluid. It is responsible for hormone production, regulating control, and emotion control. The skull, meninges, and covering skin protect the brain, while the cerebrum controls learning, thinking, reading, speech, and emotions. The brain stem connects the brain to the spinal cord. The skull also contains the cranium, which supports sense organs, face, and teeth. Brain tumors are abnormal tissue or cell growths that can cause headaches, vision problems, behavioral problems, walking problems, nausea, personality changes, difficulty concentrating, and confusion. Surgery is a common treatment, while radiation therapy and chemotherapy can also cause side effects. Region-based techniques, such as region growing and watershed algorithm, are often used to segment brain tumors in multi-spatial MRI images. These techniques involve selecting a seed, comparing it with adjacent pixels, and collecting similar pixel values. Edge-based approaches, such as foreground object marking and background spot labeling, improve segmentation results but have limitations such as over-segmentation and high computational complexity. Edge-based techniques have advantages like better output but also pose challenges such as over-segmentation and high complexity. Unsupervised brain tumor segmentation techniques include Fuzzy C Means (FCM), K-means, Gaussian Mixture Model (GMM), and Spectral clustering. These techniques have been developed to improve the accuracy of tumor diagnosis and region recognition in brain MRI images. The brain is responsible for human behavior, thinking, emotions, and perception, and abnormal cell growth can be malignant or benign. Various algorithms have been developed to segment brain MRI images under various noise conditions, including Expectation Maximization (EM) and Gaussian Mixture Model (GMM). The detection and diagnosis of Glioma brain tumors are done using machine and deep learning algorithms, such as Normalized Hidden Markov Models (NHMM) and Conventional Neural Networks (CNN). The NHMM classification method classifies the Glioma brain MRI images from non-Glioma images, while the Spectral clustering method is used to combine gray features with spatial knowledge. This paper introduces a non-invasive technique for identifying and isolating tumor areas in the brain images based on MRI scanning methods. Brain tumors are identified and diagnosed using machine learning techniques involving noise variations, Gabor transform, EML, CANFIS classifier, and NHMM classification techniques. The new CNN structure includes three Convolutional layers, two pooling layers, and one Fully Connected Neural Network (FCNN). The images produced are categorized as 'Mild' or 'Severe' based on the CNN architecture. The proposed approaches are implemented and evaluated on publicly available brain MRI images, comparing their sensitivity, specificity, and accuracy with other traditional approaches to test the efficacy of the proposed system for brain tumor detection and segmentation. The results are compared against other traditional approaches to prove the efficacy of the proposed system.

Keywords: Artificial Intelligence, Brain Tumour, Deep Learning, Machine Learning, MRI.

10.48047/jocaaa.2024.32.02.47

Introduction

The human brain is an advanced structure comprising the brain, spinal fluid, and cerebro-spinal fluid. It is accountable for producing hormones, regulating control, and emotion control [1]. The brain is defended by the skull, meninges, and covering skin. The brain is made up of the Cerebro-Spinal Fluid (CSF). The brain is protected by the skull, which is an advanced structure composed of close bones and elasticity. It is made up of three large components: the fore-brain, mid-brain, and hind-brain. The cerebrum, which is the largest part, controls learning, thinking, reading, speech, and emotions [2]. The cerebellum controls body balancing movements, and the brain stem connects the brain to the spinal cord. The meninges, skull, and cerebrospinal fluid are the brain's protective coverings. There is a section in the skull known as the cranium, which is made up of eight bones, and facial bones that support sense organs, face, and teeth. The functions of the brain are to receive, store, recall, analyze, stimulate control processes, and distribute internal and external functions. With the help of fig.1 different parts of brain has been shown.

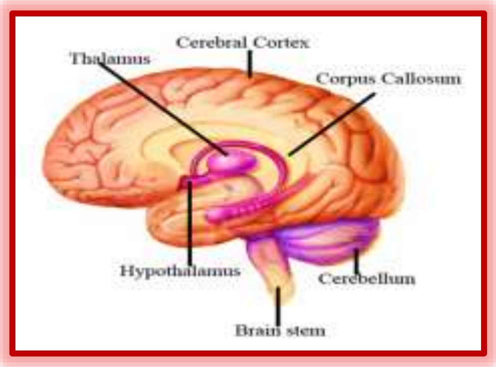

Fig.-1 Different parts of brain

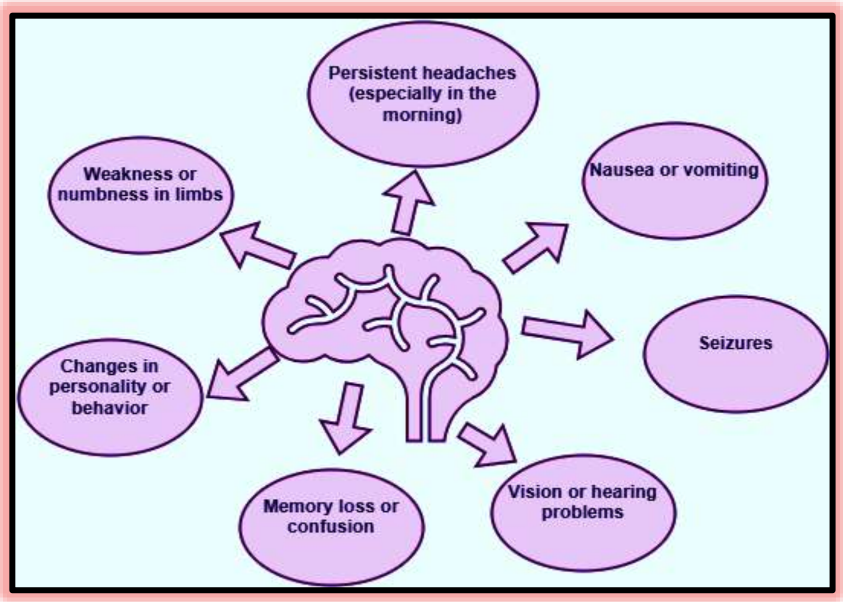

Fig.2 Early effects

10.48047/jocaaa.2024.32.02.47

Fig.2 shows the different early stage symptoms and with the help of fig.3 process of early detection has been shown.

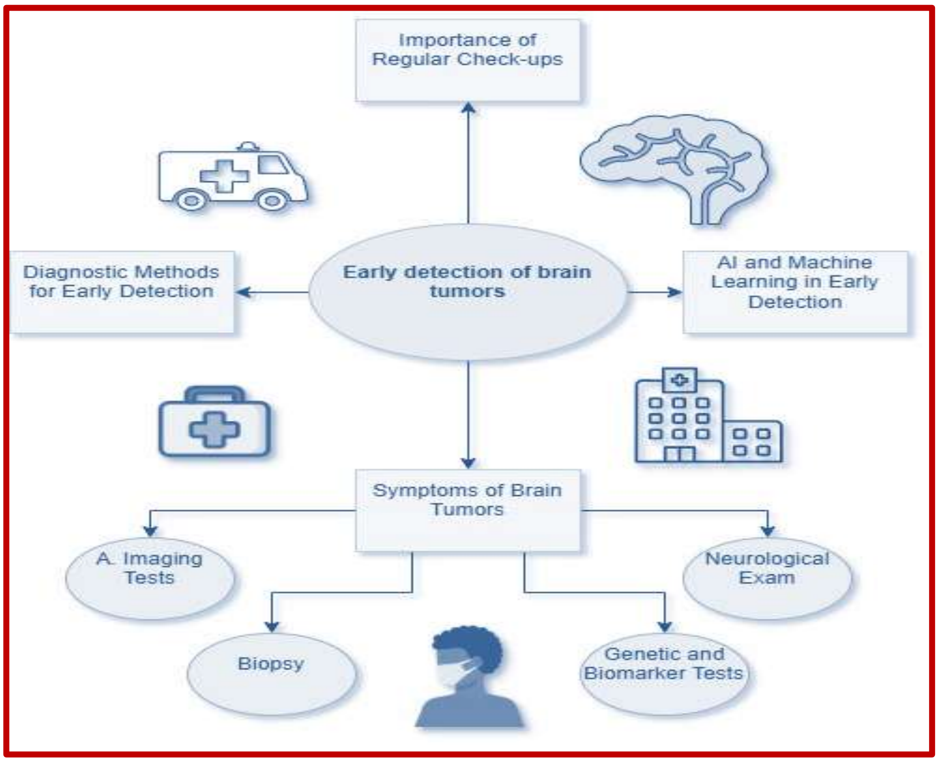

Fig.3 Early detection

Meninx, a membranous sheath of pia mater, arachnoid, and dura mater, envelops the brain and spinal cord and protect the Central Nervous System. Cerebrospinal fluid (CSF) is produced by the choroid plexus in the third and fourth ventricles of the brain, acting as a shock absorber, reducing pressure in the brain, removing waste products, and transporting hormones [3].

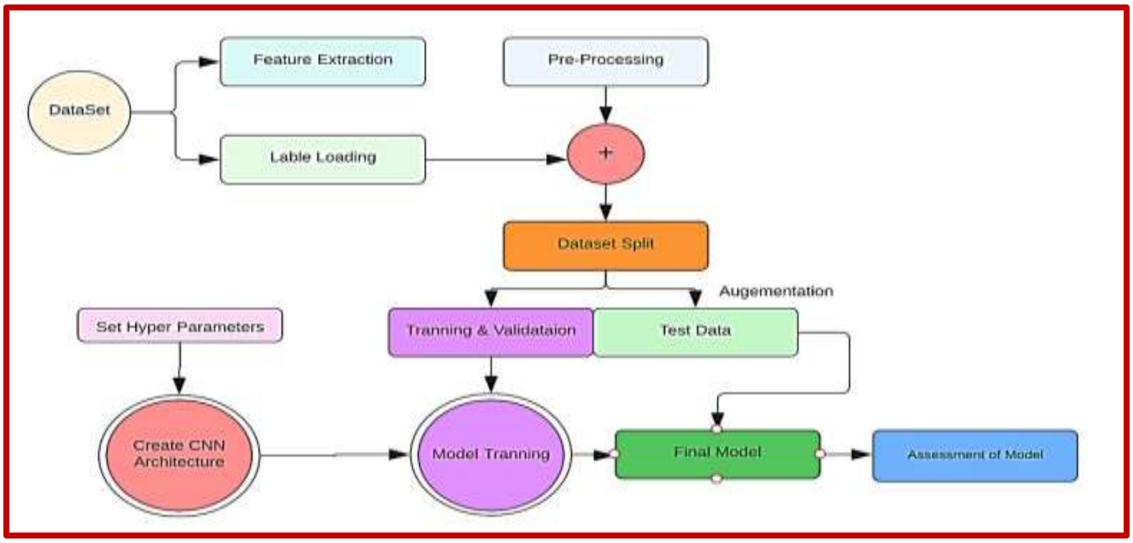

Fig.4 Process flow

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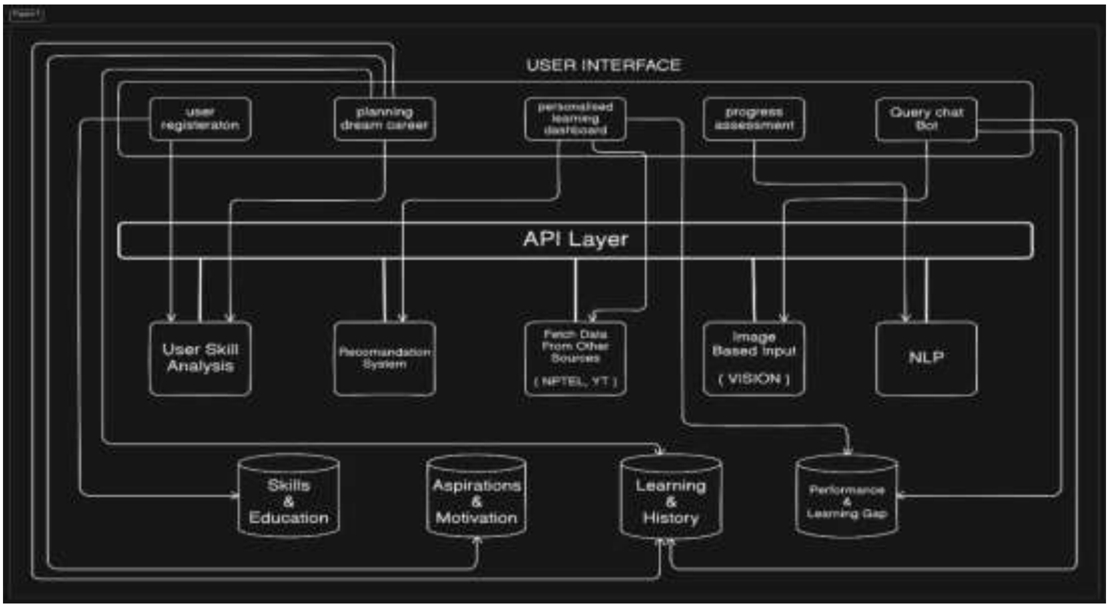

Fig.5 User interface

CNS and PNS are two components of the human nervous system. Brain tumors are abnormal tissue or cell growths in the human body, which are either benign or malignant [4]. They can lead to headaches, vision problems, behavioral problems, walking problems, nausea, personality changes, difficulty concentrating, and confusion. Surgery is a common treatment for brain tumors, where a craniotomy is done to remove the tumor without injuring other brain tissues [5]. Radiation therapy, including X-rays, gamma rays, or protons, is used to destroy the tumors. Chemotherapy, which utilizes drugs to combat cancer, can also cause side effects like headache, fever, and loss of appetite [6]. In some cases, adults with high-grade glioma can be treated with wafers. In fig.4 the process flow has been shown as well as fig.5 shows the user interface [7].

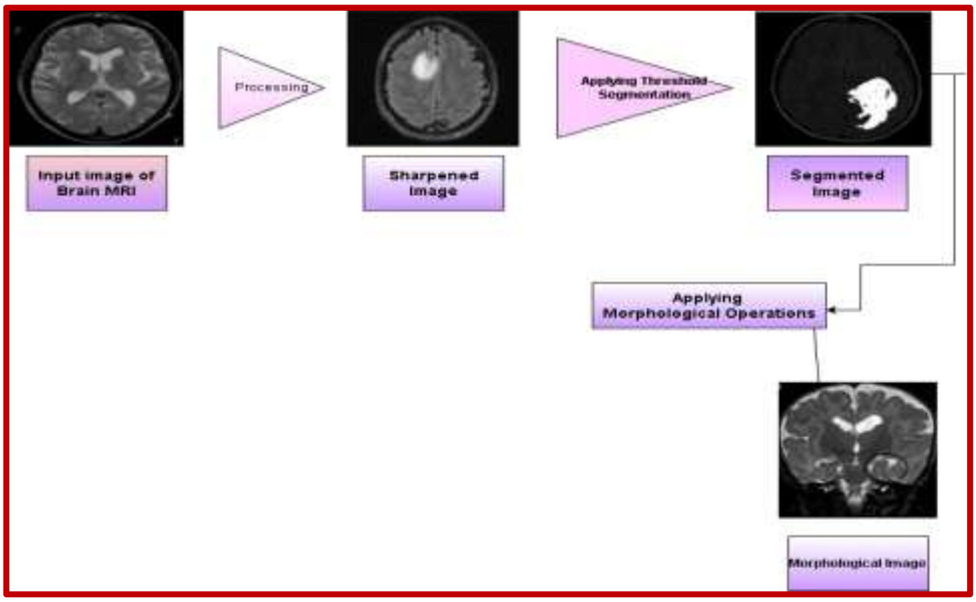

Fig.6 Step by step process

10.48047/jocaaa.2024.32.02.47

Finally, through the fig.6 step by step process has been shown. Thus, from fig.1 to 6 is more enough to understand the concept and process flow.

Literature Survey

Thresholding methods compare pixel intensities with a single standard threshold value, as per segmentation. Global thresholding is used for pre-processing and image improvement, but various intensity values can be addressed by local thresholds [8]. Over and under segmentation are the problems in multiple thresholding since global thresholds result in darker and lighter areas in the image [9].

Region-based techniques, such as region growing and watershed algorithm, are often used to segment brain tumors in multi-spatial MRI images [10]. These techniques involve selecting a seed, comparing it with adjacent pixels, and collecting a group of similar pixel values. Fuzzy information-based region development is used to define the initial seed in the region-development process, and surface-based region-developing approaches differentiate adjacent surface parameters of local pixels [11]. The region growing technique generates regions with equal pixels but has limitations such as the original seed point selection and hyper-sensitivity to noise [12].

Edge-based approaches, on the other hand, include foreground object marking and background spot labeling for improving segmentation results [13]. These techniques include color segmentation, enhanced edge detection for tumor separation, and edge location techniques. LoG files have been utilized by others to improve canny algorithm, and BCET has been utilized by others to remove noise and enhance image feature. Edge-based techniques have advantages like better output, but they pose high computational complexity, boundary-based segmentation, and high computational complexity [14].

In short, region-based techniques possess a few strengths and drawbacks while segmenting brain tumors on MRI images. But they have some limitations, too, such as over-segmentation and high complexity [15].

Unsupervised brain tumor segmentation techniques include Fuzzy C Means (FCM), K-means, Gaussian Mixture Model (GMM), and Spectral clustering. FCM was first introduced by Phillips et al. in 1995, and new concepts have been elucidated. Emblem et al. developed Fuzzy c-means-based brain tumor segmentation program, combined with other classifiers to achieve better results in segmentation. Ain et al. developed phases of tumor diagnosis and region recognition using SVM classifiers. Ji et al. developed FCM-based brain MR segmentation that is adaptive in nature, whereas Verma et al. used computational FCM to combine gray features along with spatial knowledge. Dubey et al. built upon earlier research by integrating rough set theory and FCM.

Design and Analysis

The brain is an essential organ responsible for human behavior, thinking, emotions, and perception. It produces hormones and regulates processing, awareness, attention, and emotion [16]. The skull is a sophisticated structure protecting and providing form. Abnormal cell growth can be malignant or benign. A segmentation algorithm based on automatic was introduced to segment brain MRI images under various conditions of noise utilizing Expectation Maximization (EM) and Gaussian Mixture Model (GMM). Vishnuvarthanan et

10.48047/jocaaa.2024.32.02.47

al. (2018) presented a bacteria foraging optimization based modified FCM algorithm to improve MRI brain image segmentation performance. Zotin et al. (2018) presented edge detection of brain tumors employing FCM, where Balance Contrast Enhancement Technique (BCET) was employed to remove noise and enhance image features. Gordillo et al. (2013) discussed the major types of thresholding techniques, including global and local thresholding. Viji & Jaya Kumari (2013) proposed texture-based region growing method, utilized to extract neighborhood pixels' local texture information in deriving brain tumors from ROI of MRI. Proposed CNN architecture is based on normal CNN architecture for deriving maximum classification and diagnosis accuracy [17].

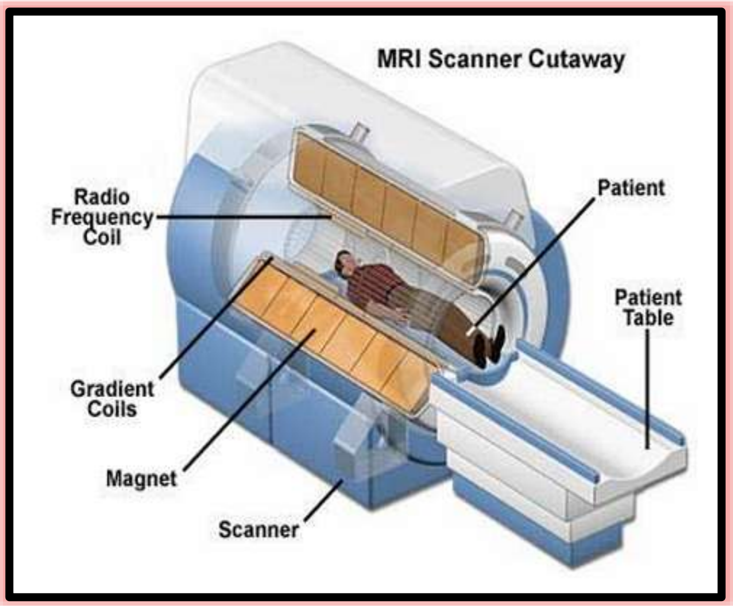

Fig. 7 Constructional parts of an MRI scanner in cross-sectional view

This paper deals with the detection and diagnosis of Glioma brain tumors using conventional methods like CT, MRI, and ultrasound scanning [18]. MRI is selected due to its high-contrast visibility. Detection and diagnosis of tumor regions in Glioma brain images are done using machine and deep learning algorithms [19]. Normalized Hidden Markov Models (NHMM) are proposed for tumor detection, and Conventional Neural Networks (CNN) are proposed for tumor diagnosis [20].

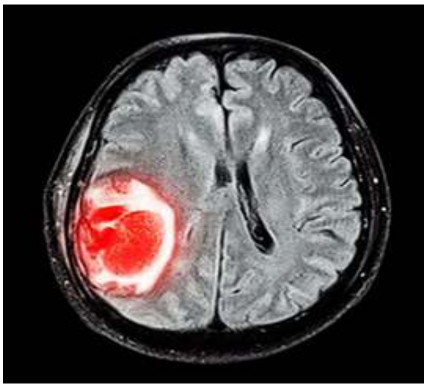

Fig.8 Image of tumor in brain

10.48047/jocaaa.2024.32.02.47

Brain MRI image tumor pixel detection is achieved using a temperature distribution algorithm. Edge boundary pixels are identified using the finite difference approach and the elimination of Gaussian noises. Glioma brain images and non-glioma brain images are classified using ensemble classification algorithms with sensitivity, specificity, and accuracy being attained in LGG and HGG images. Mathematical Morphological Reconstruction (MMR) is used in brain tumor detection with sensitivity and specificity rates of 96.7% and 96.6% respectively [21].

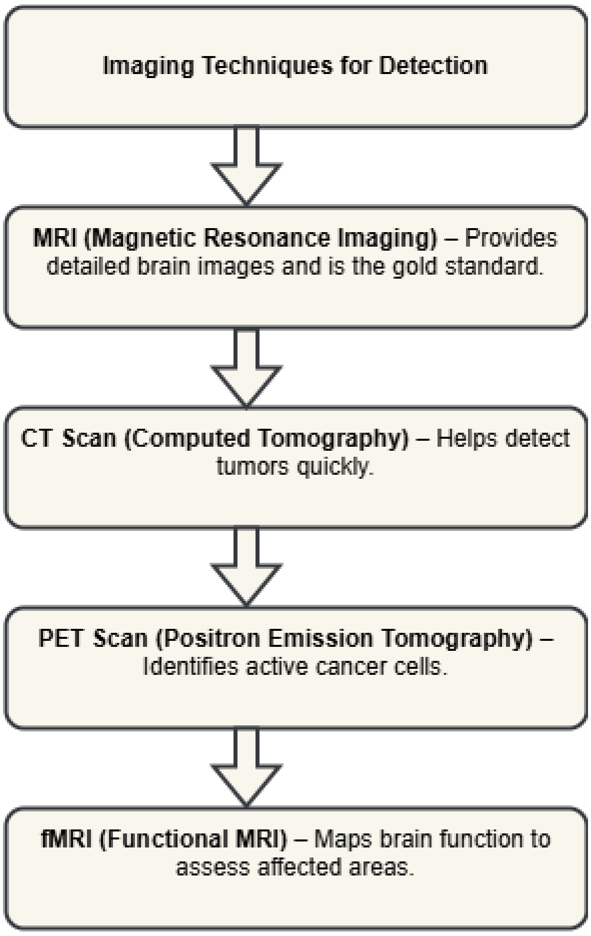

Fig.9 Step by step function and operation

NHMM classification method is used to classify the Glioma brain MRI images from the non-Glioma images. Discrete Wavelet Transform (DWT) is used to decompose the source brain image into low frequency and high frequency subband coefficients. The NHMM classification algorithm classifies the source brain images as Glioma images and Non-Glioma images, and tumor regions in the Glioma image are detected using morphological functions.Fig.7, 8 and 9 is very essential to do the analysis.

Wavelet decomposed coefficients may be obtained from the original brain MRI image by using 2D-Discrete Wavelet Transform (DWT). The wavelet function and the scale function are defined by equations. Low frequency sub bands and high frequency sub bands are produced by multiplying the original brain MRI images with wavelet and scale functions. The original brain MRI image is initially fed to Low Pass Filter (LPF) and High Pass Filter (HPF) with a down sampling factor of 2. The 'Approximate' sub band is the low frequency sub band, and all other sub bands are high frequency sub bands. The 'LL' sub band is utilized

10.48047/jocaaa.2024.32.02.47

for calculating the features for the glioma and non-glioma image classification. The coefficient matrix of the wavelet is used for run length and energy feature calculations. Four classes of publicly available datasets are used for brain MRI image feature extraction, namely Low resolution normal (Non-Glioma), High resolution normal (Non-Glioma), Low resolution normal (Glioma), and High resolution normal (Glioma).

The default CNN model for Glioma brain image classification achieved 96.56% accuracy, but that is unacceptable for tumor diagnosis. For improving the accuracy of classification, the proposed CNN architecture includes four Convolutional layers, three pooling layers, and a single Fully Connected Neural Network (FCNN). Data augmentation has been utilized for improving the size of Glioma brain images for training with techniques like right shifting, left shifting, and flipping. The suggested CNN architecture utilizes four Convolutional layers, and for each of them, there are some filters that convolve the input image with their Convolutional filter kernel. To reduce the size of the output, there is a pooling layer, and the third pooling response is transferred to the FCNN. The FCNN consists of three layers: an input layer, five hidden layers, and an output layer. The neurons in each layer are decided once the high classification accuracy is checked. The classified Glioma image is ultimately classified as either 'Mild' or 'Severe' based on the proposed CNN architecture.

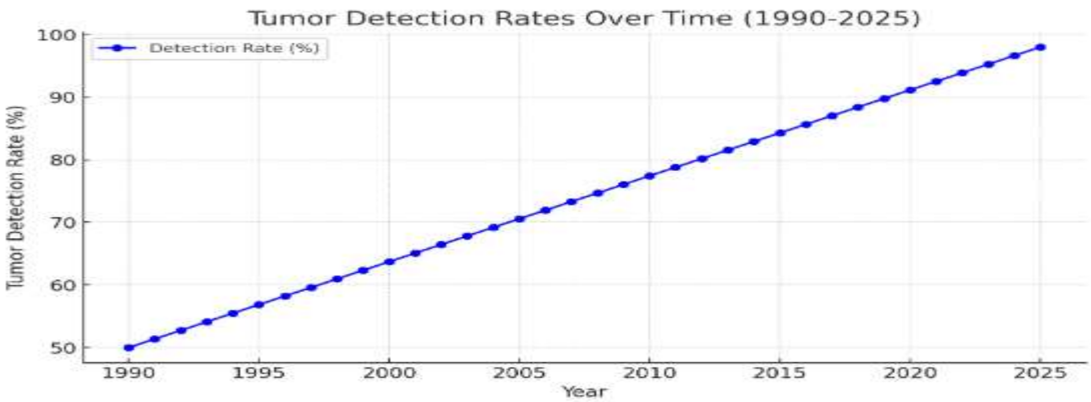

Fig. 10 Tumor detection rates

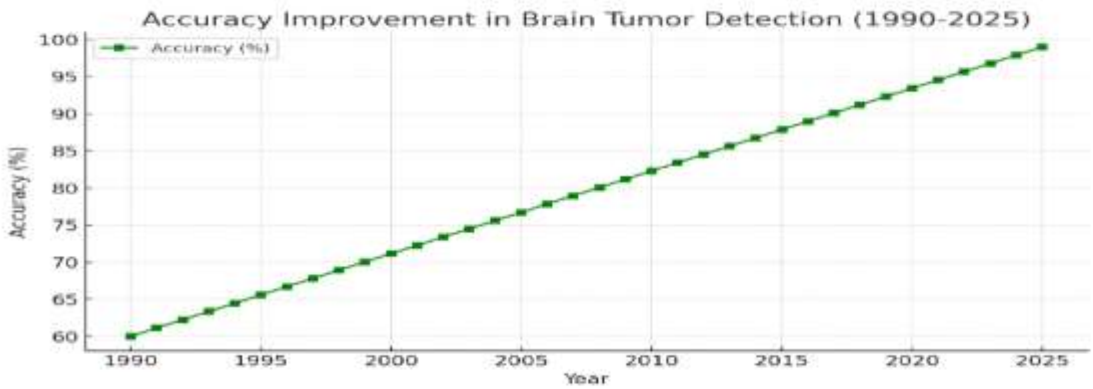

Fig.11 Accuracy improvement in brain tumor detection

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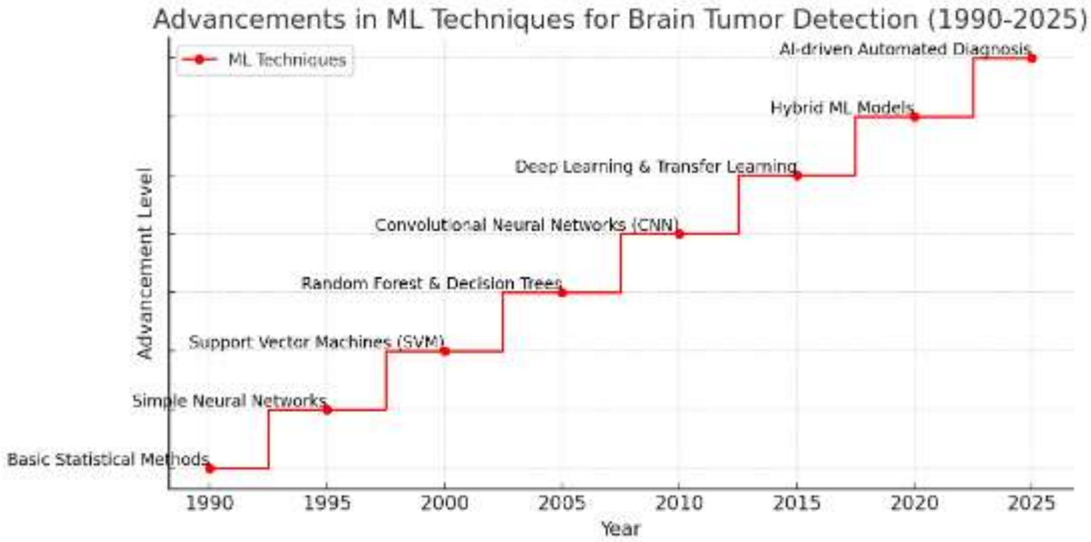

Fig.12 Advancements in ML for brain tumor detection

With the help of fig. 10, 11 and 12 the targeted results has been tried to justify.

Conclusion

This paper proposes three approaches to classify and diagnose Glioma brain images: EML, NHMM, and CNN architecture. The first approach uses the EML algorithm for Glioma image classification and CANFIS for tumor region diagnosis. The second approach uses the NHMM algorithm and deep learning algorithm for tumor region diagnosis. The third approach uses CNN architecture for both Glioma image classification and deep learning for tumor region diagnosis. The first method uses index filtering to remove noise content from source brain MRI images, converting them into multi-oriented pixels. The NHMM algorithm classifies the source brain image into Glioma or non-Glioma, and morphological functions are used to locate tumor regions. The NHMM classification algorithm achieves 98.1% of Se, 98.3% of Sp, and 98.9% of Acc on LGG images and 96.9% of Se, 97.4% of Sp, and 98.4% of Acc on HGG images. The proposed CNN architecture consists of three Convolutional layers, two pooling layers, and one Fully Connected Neural Network (FCNN), achieving an average ICR of about 99%.

Future Work

Future work will explore the use of proposed methodologies for brain tumor detection and stroke region classification in MRI images, focusing on their impact on stroke-affected images.

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