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SURVEY

Brain Tumor Detection and Classification Using Intelligence Techniques: An Overview

SHUBHANGI SOLANKI[1], UDAY PRATAP SINGH[2], (Member, IEEE), SIDDHARTH SINGH CHOUHAN[3], AND SANJEEV JAIN[4], (Member, IEEE)

[1]Department of Computer Science Engineering, LNCT University, Bhopal 462042, India
[2]School of Mathematics, Shri Mata Vaishno Devi University, Katra 182320, India
[3]School of Computing Science and Engineering, VIT Bhopal University, Sehore, Madhya Pradesh 466114, India
[4]Department of Computer Science and Information Technology, Central University of Jammu, Jammu, Jammu and Kashmir 181143, India

Corresponding authors: Shubhangi Solanki (solanki.shubhangi@gmail.com) and Siddharth Singh Chouhan (siddharth.smvdu@gmail.com)

ABSTRACT A tumor is carried on by rapid and uncontrolled cell growth in the brain. If it is not treated in the initial phases, it could prove fatal. Despite numerous significant efforts and encouraging outcomes, accurate segmentation and classification continue to be a challenge. Detection of brain tumors is significantly complicated by the distinctions in tumor position, structure, and proportions. The main disinterest of this study stays to offer investigators, comprehensive literature on Magnetic Resonance (MR) imaging's ability to identify brain tumors. Using computational intelligence and statistical image processing techniques, this research paper proposed several ways to detect brain cancer and tumors. This study also shows an assessment matrix for a specific system using particular systems and dataset types. This paper also explains the morphology of brain tumors, accessible data sets, augmentation methods, component extraction, and categorization among Deep Learning (DL), Transfer Learning (TL), and Machine Learning (ML) models. Finally, our study compiles all relevant material for the identification of understanding tumors, including their benefits, drawbacks, advancements, and upcoming trends.

INDEX TERMS Brain tumor, image classification, image segmentation, deep learning, machine learning.

I. INTRODUCTION

An unchecked expansion of brain tissues is known as a brain tumor. It produces pressure in the skull and interferes with the brain's natural functioning. Brain tumor comes in two different types: Benign (non-cancerous) and Malignant (cancerous). Among them, malignant tumors grow quickly in the brain, damage the normal tissues, and may replicate themselves in other parts of the body [1], [2], [3]. Brain tumors are graded into four different categories:

Grade I: These tumors do not spread quickly and develop slowly. These are connected to a higher chance of enhanced order and may be surgically eliminated nearly entirely. One such tumor is a pilocytic astrocytoma.

Grade II: Although they may migrate to surrounding tissues and advance to higher grades, these tumors also grow over time. These tumors may detect even though treatment is taken by the patient. An oligodendroglioma tumor is an example of an overtime growth tumor.

Grade III: The growth of these tumors has been quicker than grade II malignancies and could spread to adjoining tissues. Such tumors require post-operative chemo or radiotherapy because surgery alone would be insufficient to treat them. Aden squamous astrocytoma is an indication of such a tumor. **Grade IV:** The most dangerous and likely to spread malignant tumors are in this category. They might even use blood vessels to speed up their growth. An illustration of one of these tumors is glioblastoma multiforme [3], [4], [5].

Brain tumors must be identified in time and appropriately be classified in order to get proper treatment and endure for patients. Because of the several vulnerabilities including different shapes, sizes of tumors, appearance, positions, scanning parameters, and modalities detection of brain tumors is a very challenging job to perform [5]. To attain this

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task a number of traditional and intelligence techniques are being used. Typically, traditional approaches like Leksell Gamma Knife, Gamma Knife (GK), and Radioactive beams are helpful in diagnosing the lesions, but this process includes human involvement and is often a time-consuming task to perform [6]. For brain tumor identification, many medical imaging modalities like Computer Tomography (CT), Magnetic resonance imaging (MRI) scans, and Poisson Emission Tomography (PET) are employed. Also, A unique MR technique called chemical exchange saturation transfer (CEST) makes it possible in imaging some substances at concentrations that are too low to affect the contrast of conventional MR imaging and too low to be directly identified in MRS at usual water imaging resolution. Among them, MRI scan is a non-invasive method that shows the internal body structure with the help of magnetization and microwave pulses. For brain tumor diagnosis, three categories of magnetic resonance image patterns are used: Fluid Attenuated Inversion Recovery (FLAIR), T1 weighted, and T2 weighted. The problem of identifying and detecting tumor-infected areas using brain MRI is crucial [6].

The human visual system has a minimal ability to notice tiny variations brought on by the Magnetic Resonance Image's increased complexity (MRI). Recently, a number of investigators developed Systems for computer-aided diagnosis (CAD) to help radiologists make precise diagnoses [6]. Although Leksell Gamma Knife is a better approach to diagnosing tumors, because of the presence of necrosis in the brain the finding suffers. Therefore, effective machine learning should be adopted in order to solve this problem. Authors in [7] have proposed a novel method with the amalgamation of a Random Forest classifier along with a voxel clustering algorithm. Similarly, conventional diagnosis processes including Leksell Gamma Knife are time-consuming processes, therefore authors in [8] have introduced a semiautomated method using an unsupervised FCM clustering algorithm for accurately segmenting the lesion volume. A pipeline of four algorithms namely K-means, Fuzzy K-means and Gaussian Mixture Model (GMM), and Gaussian Hidden Markov Random Field (GHMRF) has been proposed for the segmentation of brain tumors by the authors in [9]. Authors in [10] propose a two-stage mechanism for the assessment in dose escalation and eliminate the need for multispectral MRI data to analyze the image. The proposed framework incorporates the FCM algorithm in defining a novel method named a fully automatic method for necrosis extraction (NeXt). Although ML approaches are quite efficient in handling the MRI images for accurate detection of the tumor region, with the availability of complex, large volumes of data and high computing devices, deep learning models are being cast-off for achieving advanced performance. Therefore, to understand the detailed learning mechanism of these intelligence techniques the proposed work is aimed in presenting:

1) The proposed work incorporates various deep learning and machine learning mechanisms adopted for the detection and classification of brain tumors from MRI images.

2) Study was carried out for about 100 articles collected from various sources like ScienceDirect, Springer, IEEE, etc.

3) A separate analysis of both approaches has been carried out and various findings are tabularized individually.

4) Further, a research gap analysis has been carried out to differentiate between the importance of DL over ML.

5) Various findings like datasets, deep models, classification approaches, parameters, future research directions along with the importance of using 3D models and attention-based mechanisms are being discussed followed by our proposed work.

Organization of manuscript: introduction in section I is followed by a literature review given in section II. It includes the various studies categorized among DL and ML in a separate section. A research gap analysis of the underlying technologies is also been given in this section. Further, the various findings are given in Section III. Section IV demonstrates our proposed work. The manuscript ends with a conclusion followed by references.

II. LITERATURE REVIEW

A. DEEP LEARNING TECHNIQUES

In recent years, a lot of research has been directed toward the adaptation of deep learning models in diagnosing brain tumors. Academicians have put in their efforts and with the help of high-end computing devices, higher accuracy has been achieved. Convolutional neural networks (CNN), which include input, output, hidden layers, and hyperparameters, are often called Deep Learning (DL) [5]. It uses supervised classification and generates feature maps by having the kernel convolve all around the input image. Automatic-based feature extraction is both possible with DL models. Apart from its usefulness for medical condition detection, it has some shortcomings, including the requirements to design complex models, fine-tuning of hyper-parameters, the requirement of large data set, and time and effort to training/testing. As per recent research, significant data augmentation methods like resizing, rotation, scaling, and transformation are enforced to tackle the big data availability problem. A trained NN is used in transfer learning techniques to extract similar properties from an application-specific dataset [1]. For brain tumor identification current TL methods like RESNET-100, VGGNET, Google-Net, AlexNet, etc. are applied. The various deep-learning techniques used by the researchers in the past are summarized in Table 1.

With the recent developments in technology, 3D scanning is also being used for the analysis of tumors. 3D image processing for brain tumor detection and classification has been described in [48]. It used various deep learning frameworks, such as MobileNetV2, MobileNetV3 small, MobileNetV3 big, VGG16, VGG19, and custom CNN models. CNN achieved the highest accuracy. It offers a solution that combines a CNN built with Keras and Tensor flow with a fully-featured cross-platform application built with

TABLE 1. Brain tumor detection using deep learning techniques.

Reference	Methodology	Algorithms	Accuracy	Dataset used
Machiraju Jaya Lakshmi et al. [1]	Brain tumor classification using Softmax classifier	Inception -V3	89.00%	3064 MRI images
Wen Jun & Zheng Liyuan [2]	Brain tumor Classification using attention mechanism	CNN	98.61%	3043 MRI images
Arshia Rehman et.al. [3]	Three-layer architecture of CNN with transfer learning technique	VGG-16 and CNN	98.69 %	MRI brain slices of 233 patients
Tharindu Fernando [4]	Theoretical examination of common deep learning algorithms for detecting medical anomalies	Various Deep and machine learning techniques	NA	Biomedical images, electrical biomedical signals, and other biomedical data such as data from laboratory results, audio recordings, and wearable medical devices
Alexander Selvikvåg Lundervold et. al. [5]	Supervised learning was used across the MRI processing pipeline from acquisition to retrieving, segmentation to illness prediction	Quantitative susceptibility mapping and CNN	95.20%	Various Data sets of brain MRI
Yun Jiang et al. [11]	Multiscale CNN based statical threshold pattern techniques	Convolutional Neural Network technique	86.30%	MICCAI BRATS2015 dataset
Dongnan Liu et al. [12]	Multi-dimensional image data processing on network portals	Deep Convolutional Neural Network (DCNN)	86.50%	MICCAI BRATS 17 Challenge
Muhammad Waqas et. al. [13]	Deep CNN has been used for the organization	CNN earning Methods	NA	Positron Emission Tomography (PET) images tool is used for assessing brain tumors and differentiating tumor progression from reactive changes
Yakub Bhanothu et. al. [14]	Detection and classification using CNN	CNN	77.60%	The chosen MR image dataset consists of three classes namely glioma, meningioma, and pituitary tumors.
Zhiguan Huang, et. al. [15]	Convolution Neural Network has been used with various optimization and different activation functions for the analysis of complex tumors.	Deep CNN	95.50%	A brain tumor dataset provided by Nanfang Hospital, Guangzhou, China, and General Hospital, Tianjing Medical University, China, from 2005 to 2010
Nyoman Abiwinanda et al. [16].	Convolutional Neural Network	Deep CNN	84.20%	A brain tumor dataset consisting of 3064 T-1 weighted CE-MRI images publicly available via figshare Cheng
Ali Ari and Davut Hanbay [17]	Convolutional Neural Network	ELM-LRF	97.20%	Digital Imaging and Communications in Medicine (DICOM) file format. cranial magnetic resonance (MR) images were classified as benign or malignant by using ELM-LRF.
Yota Ishikawaet et al. [18]	Deep CNN, PNN and PNN	Binarization algorithm with water shade feature extraction model	98.50%	The number of brain cell images of our dataset is 720, and its ratio of astrocyte to low-grade astrocytoma is one-to-one, so each class has 360 images
Heba Mohsen et al. [19]	Deep Neural Network (DNN)	PCA and DWT classification	96.90%	Human brain MRIs with 22 normal and 44 abnormal images which are glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors collected from Harvard Medical School
Justin S. Paul et al. [20]	Numerous Deep learning techniques and Machine learning techniques	CNN	91.40%	brain tumor dataset
Yan Xu et al. [21]	Deep CNN with various Instigation Structures	Various deep learning frameworks for features extraction and classification	97.50%	The training data is provided by the organizers from the TCGA web
Kaoutar B. Ahmed et al. [22]	Deep Convolutional Neural Networks (DCNNs)	Fine-Tuning	81.00%	Dataset provided by the H. Lee Moffitt Cancer Research Center

TABLE 1. *(Continued.)* **Brain tumor detection using deep learning techniques.**

Mustafa Rashid Ismael [23]	Deep Neural Networks	Classification of tumors using SoftMax and sparse autoencoder	94.00%	Brain MRI slices were collected from Nanfung Hospital in Guangzhou, and the General Hospital of Tianjing Medical University in China during the period from 2005 to 2010
Renhao Liu et al. [24]	DCNN	Detail feature classification of brain tumor Magnetic Resonance	95.40%	MRI dataset. From top to bottom, they are TI-weighted (post gadolinium), T2-weighted, FLAIR, and ADM from the H. Lee Moffitt Cancer Research Center.
Nøhr Ladefoged et al. [25]	CNN	RESOLUTE and DeepUTE	67.105	NA
Himar Fabelo et al. [26]	2D CNN	Multi-layer CNN	80.30%	NA
Yuexiang Li & Linlin Shen [27]	CNN	Multi-view DNN	88.00%	BraTS 17 dataset is utilized.The data contains multimodal MRI scans of glioblastoma (GBM/HGG) and lower-grade glioma (LGG).
Lina Chato & Shahram Latifi [28]	Normal discriminant analysis	SVM, KNN, LR, and different learning algorithms.	68.80%	The glioma brain dataset was provided by the BraTS 2017 Challenge
Virupakshappa & Basavaraj Amarapur [29]	Artificial Neural Network (ANN)	Modified Level Set approach	98.00%	The BRATS database contains four sequences of MRI images for every patient which includes FLAIR, T1, T1 with Contrast, and T2 weighted images. The BRATS 2015 database.
Eze Benson et al. [30]	CNN	Heterogeneous feature for classification	92.00%	The dataset of BraTS 2018
Chenhong Zhou et al. [31]	CNN	U-Nets were deepened by adding double convolution layers, emergence modules, and dense modules	81.35%	Dataset of BraTS 2018 challenge
Geena Kim [32]	2D Fully CNN	CNN Architecture	88.20%	BRATS15 and BRATS17 dataset
Parnian Afshar et al. [33]	Feature extraction with DCNN	Capsule Networks (Caps Nets)	86.56%	Brain Magnetic Resonance Imaging (MRI) image
Peter D. Chang [34]	Feed Forward Neural Network	Fully connected CNN	87.40%	BRATS 2016 challenge
Fabian Isensee et al. [35]	DCNN	U-Net Architecture	90.10%	BraTS challenge
Sanjay Kumar et al. [36]	Deep-CNN	UNET Architecture	89.60%	Brats Dec 2017 dataset (a)T (b) T1 contrast-enhanced (c) T3 (d) flair
AM. Hasan et.al [37]	A deep learning approach to feature withdrawal may be used to excerpt information from MRI brain images. To extract customized features, use MGLCM	Hybrid deep learning features Collaborative deep learning features are used	99.30%	MRI axial slices from Iraqi center for research and magnetic resonance of Al-Kadhimain Medical Cit
S. Deepak et.al [38]	Deep learning approaches of training models for feature extraction	Deep CNN-SVM	97.10%	Figshare dataset and brain MRI images
Hari Mohan Rai & Kalyan Chatterjee [39]	U-net model and VGG-16	CNN	98.00%	MRI dataset with cropped and uncropped images
Deepak V.K & Sarath R [40]	Brain tumor Segmentation using deep learning with cascaded regression technique	Fully CNN	-	BRATS 2018 dataset
Ejaz Ul Haq et.al. [41]	Data augmentation technique	CNN	97.30%, 96.50%	Figshare and BRATS 2018 dataset
Sidra Sajid et.al. [42]	Deep learning	CNN	86.00%	BRATS 2013 dataset

TABLE 1. *(Continued.)* **Brain tumor detection using deep learning techniques.**

Ramin Ranjbarzadeh et. Al [43]	Brain tumor segmentation using deep learning and Attention-based mechanism	Cascade CNN	92.03%	BRATS 2018 dataset
T. Ruba et.al [44]	Brain tumor segmentation using novel LSIS operator from 3D MRI images	Cascaded CNN,3D U-net	-	BRATS 2015
Aman Verma et al. [45]	Brain tumor classification using deep model	CNN	97.87%	MRI images
Praveen Kumar Ramtekkar et. al [46]	Brain tumor detection using CNN	CNN	98.9%5	MRI images
R. Rajasree et al. [47]	Brain tumor classification using deep learning	U-NET, CNN	96.36%	BRATS 2015

PyQt5 and MariaDB, all of which are designed for usage in medical settings like hospitals and clinical images. The primary goal of this work is to characterize a brain damaged by a tumor using real-world data and identify abnormal pixels [51]. In [52] authors describe a pre-processing, data augmentation, segmentation, and binary classification of brain tumors implemented with a 3D medical image. In this context, classification is performed using two distinct classifiers: Dense-Net and Dark-Net. On the BRATS 2018 dataset of 3D-MR images, the suggested framework obtained an accuracy of 98.67% and a dice similarity coefficient (DSC) of 97.91% for segmentation. For brain tumor classification on 3D-MR images from the BRATS 2018 dataset, the suggested framework obtained a DSC of 98.14%, an accuracy of 98.26% using the Dense-Net classifier, and a DSC of 96.4%, an accuracy of 96.52% using the Dark-Net classifier. A higher level of accuracy was achieved by the Dense-Net classifier compared to the Dark-Net classifier. In addition, they have compared this framework to earlier research, and the results show that custom CNN obtains higher classification accuracy. Some of the 3D-based methods are given be Table 2.

B. MACHINE LEARNING METHODS

Pre-processing, segmentation, extraction of features, and categorization are the four key phases of ML techniques used to diagnose brain tumors.

1) PREPARATION

To produce accurate diagnoses in the clinical field, precise imaging is essential. The efficiency of clinical images is influenced by the artifact acquisition methods, like magnetic resonance scans, CT, and PET. A Magnetic resonance scan's real images could contain a lot of unwanted and pointless details. Magnetic resonance imaging is impacted by Rician noise [36]. It is challenging to remove Rician distortion since it is signal-sensitive. Pre-processing techniques including filtration, intensity correction, and skull stripping is being used to maintain the original visual characteristics.

2) SEGMENTATION

It is a technique used to obtain areas of interest from digital images. The tumor's position must be distinguished from the MR brain scans, which is crucial. For segmentation, numerous supervised methods are available, including thresholding, soft computing technique, atlas-based, Neural Networks (NNs), clustering, etc. Thresholding methods include global, adaptable, Otsu's, and histogram-dependent techniques. There are two unsupervised clustering methods namely K-means clustering and fuzzy C-means clustering. It successfully separates brain MRI scans into Gray Matter (GM), Cerebrospinal Fluid (CSF) as well as White Matter (WM). Segmentation techniques that draw inspiration from nature include Particle Swarm Optimization (PSO) and Genetic Algorithm. Recent studies show that DL frameworks like Convolutional Neural Networks (CNN), Mask- Recurrent Neural Networks, and UNET outperform conventional methods in segmentation.

3) FEATURE EXTRACTION

While extracting features, properties of brain MR scans such as shape, structure, wavelet, and Gabor are retrieved. The Gray-Level Co-occurrence Matrix (GLCM) is commonly studied. A second-order statistical method is used to evaluate textural features like energy, correlation, and intensity. Wavelet data is derived using the Discrete Wavelet Transform (DWT). The approximation coefficients are obtained and it is applied to an original image, and then the feature vector is selected. Both automatic features produced by DL techniques like Convolutional Neural Networks, ResNet, Capsule Networks, and handwritten features have shown success. To decrease the number of features, PCA and Genetic Algorithms are utilized.

4) CLASSIFICATION

Benign and malignant tumors are the most prevalent forms of brain tumors. The three types of malignant tumors include hypothalamic, gliomas, and malignant tumors. Table 3 shows a summary of some ML methods.

TABLE 2. Brain tumor detection using 3d deep learning techniques.

Reference	Methodology	Algorithms	Accuracy	Dataset used
Md. Akram Hossan Tuhin et. al. [48]	3D MRI, MRSI, and CT images are used for the detection of brain tumors using CNN and the detection of the tumor using segmentation methods	CNN and 3D CNN	85.005	Real-time hospital image dataset
Rudresh D. Shirwaikar et. al. [49]	3D CNN-based brain tumor segmentation, tumor detection, and classification	Various machine learning and deep learning classifiers.	-	Some real-time and some synthetic datasets are utilized
H. Yahyaoui et. al. [50]	DensNET using custom CNN for brain tumor detection	3D CNN , DENSENET model	92.06%, 85.00%	2 Heterogenous dataset including 3D and 2D real-time images
Pokhrel S et. al. [51]	3D image processing for brain tumor detection and classification	MobileNetV2, MobileNetV3 small, MobileNetV3 big, VGG16, VGG19,	92.00 %-95.00%	Ream word brain image dataset
Gull S and Akbar S [52]	Binary classification of brain tumors has been implemented with 3D medical image	Dense-Net and Dark-Net based CNN	96.52%	BRATS 2018
Yannick Suter et al. [53]	3 Dimensional CNNs	SVM with heterogeneous feature extraction in CNN classification	72.20%	BraTS 2018
Yan Hu & Yong Xia [54]	DCNN	3D-based deep CNN	81.40%	BraTS 2017 Challenge dataset
Dong Nie et al. [55]	Classification using 3D deep Convolutional Neural Network	3D multi-level representation and organization by using CNN	99.60%	Brain images (i.e., T1 MRI, fMRI and DTI) of high-grade glioma patients.
Anand kumar & P.V. Shridevi [56]	Brain tumor segmentation using 3D deep learning	3DCNN	99.8%	BRATS 2015
Girija Chetty et.al. [57]	Medical image analysis by using 3D deep learning	3D U-NET	-	BraTS Challenge 2018 dataset
Zeeshan Shaukat. et al. [58]	Semantic segmentation using 3D deep learning	3D U-NET	Dice score-95%	BRATS dataset
Hiba Mzoughi. et al. [59]	Brain Tumor Classification using 3D multiscale.	3D CNN	96.49 %	BRATS 2018 dataset
Joseph Stember & Hrithwik Shalu [60]	Classification of 3D MRI brain tumors	Deep Reinforcement learning	100% testing set accuracy	3D MRI images
Yohan Jun et al. [61]	Detection of metastatic brain tumors using deep learning 3D black blood technique	3D CNN	97.08% and sensitivity-100%	Clinical data.
Pranjal Agrawal.et.al. [62]	Segmentation and classification using 3D deep learning	3D U-net, Deep CNN	90%	MRI Kaggle dataset
Agus Subhan Akbar.et.al [63]	U-net architecture for brain tumor segmentation	Residual attention block mechanism	77.73%, 82.19%, 89.33%	BRATS 2018,2019,2020,2021 challenge database

C. GAP ANALYSIS OF ML AND DL METHODS

Further, to analyze the research gap between the existing machine learning and deep learning approaches, the study has been directed towards summarizing the various literature work incorporating both technologies which are presented in Table 4. This table compromises the details with respect to methodology, algorithms, gap analysis, and dataset used by the authors.

III. FINDINGS

Expert radiologists do brain tumor segmentation and classification. ML and DL may help radiologists to make better decisions. This paper summarizes current strategies for automated brain tumor categorization. Histogram equalization, median, Gaussian, and Wiener filters preprocess MRI images. There are six forms of segmentation: clustering, statistical, CNN, region, and threshold-based [37]. K-means Researchers often utilize C-means clustering and adaptive global thresholding.

TABLE 3. Machine learning methodologies for brain tumor detection.

Reference	Methodology	Algorithms	Accuracy	Dataset used
HT. Zaw et.al [64]	Naive Bayes classification successfully identifies a tumor location with all propagating malignant tissues	Naive Bayes (NB) classification	94.00%	REMBRANDT database for brain cancer imaging contains MRI images
E. Sert et.al [65]	Extracted features, as well as classification, are done using the training to the model architecture and support vector machine, correspondingly	The maximum entropy calculation method has been used	95.00%	Brain tumors in MRI images
TL. Narayana et al. [66]	Multi-objective genetic heuristic optimizing and SVM on brain MRI images	Segmentation, Feature Extraction, and SVM Classification	91.23%	Datasets provides different MRI images such as T1-W, T2-W, PD, and FLAIR
FP. Polly et.al [67]	The computerized system employs k-means for clustering used for feature extraction with principal component analysis and discrete wavelength transform	Clustering, Segmentation, Feature Extraction and Reduction, and SVM Classification	99.00%	DATABASE OF HGG AND LGG TUMOR.
J. Amin et.al [68]	A computerized brain magnetic resonance approach may distinguish malignant from noncancerous lesions	SVM Classification	98.00%	datasets such as Harvard, RIDER and Local.
N. Gupta et.al [69]	Non-invasive and adaptable tumors identification approach using T2-weighted brain MR images. Entropy measures two important textural and form aspects from the segmented picture. SVM classifies MR images using key properties	Support vector machine (SVM) classifies	98.90%	Dataset collected from MP MRI & CT Scan Centre at NSCB Medical College, Jabalpur
N. Gupta et.al [70]	Naive Bayes-based decision support system detects and grades tumor severity	Naive Bayes	97.83%	Glioma tumors images collected from NSCB Medical College Jabalpur, India, and BRATS dataset brain MR images.
A.Minz et.al [71]	Preprocessing, feature extraction, and classification using CNN	GLCM features ML and DL-based algorithms	89.90%	
AS. Shankar et.al [72]	Gustafson-Kessel fuzzy clustering. Gray Level Co-occurrence Matrix extracts MRI image features (GLCM)	Gustafson-Kessel (G-K) fuzzy clustering	95.00%	NA

Deep learning-based segmentation allows for more precise tumor extraction [26]. GLCM and DWT largely extract features. GLCM returns texture characteristics, whereas DWT returns approximation coefficients. Deep learning architectures automate feature extraction. ResNet [4], [11]. PCA and bio-inspired algorithms like PSO are used to reduce dimensionality. Choosing the optimal characteristics for categorization is challenging. Hence a hybrid technique integrating several features is utilized. ML and DL techniques are used to classify data. multi-kernel SVM Binary classification uses linear, RBF, and Cubic. These findings are comparable to VGG19 and ResNet. ANFIS, a fuzzy-ANN hybrid, performs better for binary classification. However, the database does not capture all tumor forms and grades. Or they have to obtain MRIs from nearby hospitals. As a result, comparing the performance of various approaches is difficult. A common database of all tumor kinds is required for future study. The deep learning approach can extract more detailed features from the dataset for segmentation and classification. Transfer learning techniques provide better prediction results for deep learning approaches in the effective detection of brain tumors. The machine learning approach gives better performance when the dataset is small, whereas, with large datasets deep learning, models are efficient. The deep learning approach used several pre-processing techniques like scaling and normalization to enhance desired features. Preprocessing techniques of machine learning including filtration, intensity correction, and skull stripping are being used to maintain the original visual characteristics with a limited data set. The primary drawback of machine learning technology is that it is complicated, with a large number of parameters increasing with the execution time and system requirements for implementation. The deep learning approach offers low complexity, where the features are self-learned by the network. Figure 1 and Figure 2 demonstrate the valuation of Machine Learning and Deep Learning methods over accuracy.

Further, the various findings from the literature are being discussed in separate categories like datasets used, different tumor classification approaches, deep learning models, parameters used, limitations of existing approaches, and future research directions.

A. DATASETS USED

The researchers make use of a variety of datasets that are available to the general public in order to test the proposed

TABLE 4. Gap analysis of machine learning and deep learning methods.

Reference	Methodology	Algorithms	Gap Analysis	Dataset used
Tharindu Fernando [4]	Theoretical examination of common DL methods for detecting medical anomalies.	Various ML and DL methods	It is a theoretical evaluation only	PhysioNet/CinC 2016 dataset
Alexander Selvikvag Lundervolda et al. [5]	Supervised learning was used across the MRI processing pipeline from acquisition to retrieving, segmentation to illness prediction	Quantitative susceptibility mapping and CNN	Various heterogeneous features are considered for model training which generates redundancy issues.	Image synthesis in MRI
Yun Jiang et al. [11]	The Multiscale Convolutional Neural Networks (MSCNN) with Statistical Thresholding	Deep CNN	High communication cost for multiple hidden layers	MICCAI BRATS 2015 dataset
Dongnan Liu et al. [12]	CBICA's Image Processing Portal uses a 3D Large Kernel Anisotropic Network.	Deep CNN	It is applicable for the CBICA dataset only not work for real-time datasets.	MICCAI BRATS 17 Challenge
Muhammad Waqas Nadeem, Mohammed A. Al [13]	Deep CNN has been used for the classification	Deep Learning Methods	Conventional pretrained CNN modules are used.	Brain tumor
Yakub Bhanothu, Anandha narayanan Kamala kannan, Govindaraj Rajamanickam [14]	For the detection and categorization of diseases in MRI scans, CNN has been employed.	CNN with various VGG modules such as VGG16 and VGG32	Generate high-time computation when it deals with 50 and 100-deep layers.	MR image dataset
Zhiguan Huang et al. [15]	With a Modified Activation Function, a CNN Based on Complicated Networks for BT classification	modified CNNBCN, ResNet, DenseNet and MobileNet	Generates good results for the RESNET-101 module only.	A brain tumor dataset provided by Nanfang Hospital, Guangzhou, China, and General Hospital, Tianjing Medical University, China, from 2005 to 2010
Nyoman Abiwinanda et al. [16]	CNN using deep learning method	Convolutional Neural Networks (CNNs) come in several shapes and dimensions. VGG16, ResNet, AlexNet	Different feature extraction methods are used that select non-essential and redundant features sometimes	a brain tumor dataset T-1 weighted CE-MRI images publicly available via figshare Cheng
Ali Ari & Davut Hanbay [17]	Deep CNN for classification	ELM-LRF Based Extreme Learning Machine	Low accuracy for all experiments	images are in Digital Imaging and Communications in Medicine (DICOM) file format. cranial magnetic resonance (MR) images were classified as benign or malignant by using ELM-LRF.
Heba Mohsen et al. [19]	Deep Neural Network	Principal Components Analysis (PCA) and Discrete Wavelet Transform (DWT)	Low accuracy for both PCA and DWT	human brain MRIs images from Harvard Medical School
Yan Xu et al. [21]	Features of Deep Convolutional Activation	Deep Convolutional Activation Features were trained using the information from Datasets	ImageNET deep framework has been used to generate overfitting issues with different optimizers.	The training data is provided by the organizers from the TCGA web
Kaoutar B. Ahmed et al. [22]	CNN using the deep learning methodology	Fine-Tuning	High error rate	Dataset provided by the H. Lee Moffitt Cancer Research Center
Mustafa Rashid Ismael [23]	Deep-NNs	Softmax with the Stacked Sparse Autoencoder (SSA)	High-time computation for deep layers	brain MRI images and BRATS dataset
Nøhr Ladefoged et al. [25]	CNN	RESOLUTE and DeepUTE	Low accuracy and dice score	-
Himar Fabelo et al. [26]	2D-CNN	Multi-layer CNN	High computation when a large number of conventional layers are used	-
Yuexiang Li & Linlin Shen [27]	CNN	SPNet and the Multi-view Deep Learning Framework (MvNet)	Time consuming process that generates similar results as CNN	BraTS 17 dataset is utilized.The dataset contains multimodal MRI scans of glioblastoma (GBM/HGG) and lower-grade glioma (LGG).

TABLE 4. *(Continued.)* Gap analysis of machine learning and deep learning methods.

Lina Chato & Shahram Latifi [28]	Deep learning was used to create the CNN and Linear Discriminant (LD).	Machine learning algorithms include the support vector machine, LD	Conventional machine learning methods are used	The glioma brain dataset was provided by the BraTS 2017 Challenge
Virupakshappa & Basavaraj Amarapur [29]	Adaptive-ANN	Modified Level Set approach	Low accuracy and overfitting problem	The BRATS database contains four sequences of MRI images for every patient which includes FLAIR, T1, T1 with Contrast and T2 weighted images. The BRATS 2015 database.
Eze Benson et al. [30]	Deep CNN module	Pyramid form is used in Hourglass structure		The dataset of BraTS 2018
Chenhong Zhou et al. [31]	Deep learning-based CNN	From a range of angles, OM-Net is used to enhance performance	Both CNNs are conventional modules	Dataset of BraTS 2018 challenge
Geena Kim [32]	2D Fully CNNs	Double convolution layers, dense, and inception modules were added to a U-Net to create a deep architecture	Fully CNN may take high computation, it required HPC and GPU environments.	BRATS15 and BRATS17 dataset
Parnian Afshar et al. [33]	CNNs- based deep learning	Capsule Networks (CapsNets)	Low accuracy when evaluated with heterogeneous datasets.	brain Magnetic Resonance Imaging (MRI) image
Peter D. Chang [34]	Fully CNNs	Semantic segmentation with a fully convolutional neural network (FCNN)	Feed Forward model has been used it generates similar accuracy as ANN	BRATS 2016 challenge
Fabian Isensee et al. [35]	Convolutional Neural Networks	UNET is semantic segmentation architecture.	Segmentation features are used for module training that may not match generating the background knowledge	BraTS challenge
Sanjay Kumar et al. [36]	Fully CNNs	Deep CNN with different optimizers	High computation when epoch size is high	Brats Dec 2017 dataset (a)T (b) T1 contrast-enhanced (c) T3 (d) flair
Yan Hu & Yong Xia [54]	Deep learning-based DCCN	Cascaded U-Net 3D DNN-based Technique	DNN generates low accuracy over CNN and DCNN	BraTS 2017 Challenge dataset
Dong Nie et al. [55]	DL-based 3D CNNs.	3-dimensional multi-channel architecture CNNs for data transfer and Support Vector Machine	High-time computation for channel mapping and feature selection in each channel	brain images (i.e., T1 MRI, fMRI, and DTI) of high-grade glioma patients.
Subhashis Banerjee et.al. [74]	In addition to classification, CNN has been used for a variety of feature extractions	Deep Convolutional Neural Networks (ConvNets)	Different optimizers varied the result for accurate detection of normal as well as anomaly	BraTs 2017 dataset
Asma Naseer et. al. [75]	A Convolution Neural Network (CNN)-based early brain tumor detection using six distinct datasets.	CNN and CAD are deep learning-based algorithms.	Overfitting problems generate when it deals with cross-model detection	a benchmark dataset, BR35H, containing brain tumor MRIs. six different datasets, i.e., BMI-I, BTI, BMI-II, BTS, BMI-III, and BD-BT.
Isselmou Abd El Kader et.al. [76]	Deep CNN has used 400 hidden layers and numerous SoftMax functions	Deep wavelet Auto-Encoder model	Homogeneous encoder features are extracted only not considering other features	MR brain images from BRATS2012, BRATS2013, BRATS2014, BRATS2015, 2015 challenge, and ISLES
Lilly Sheeba et. al. [77]	By segmenting grayscale images, the Otsu approach has been used to locate brain tumors.	Segmentation using Otsu	Otsu methodology works on homogeneous features only	MRI brain images.
Javaria Amin et. al. [78]	A comprehensive study for brain tumors using MRI, including anatomy of brain tumors and publicly accessible datasets	For brain tumor analysis, image enhancement techniques, segmentation, extraction of features, classification, DL & transfer learning, and quantum ML are used.	It is an overview-based approach and theoretical results are discussed; no real implementation is there	Datasets for brain tumor detection
Mohd Shahajad, Deepak et al. [79]	SVM feature extraction for brain tumor MRI image categorization	SVM	Old conventional SVM has been used that not able to extract deep features	MRI images from the Kaggle dataset
Esther Alberts et al. [80]	SVM, MLP, RF, KNN, and PCA based on ML	LBP, BRIEF, and HOG	-	a brain tumor dataset from “The Cancer Imaging Archive” (TCIA)

TABLE 4. ***(Continued.)*** **Gap analysis of machine learning and deep learning methods.**

Iqbal, S et al. [81]	Segmentation and clustering	Several visual characteristics are retrieved and examined	Old features extraction and selection methods are used	brain tumor multi-classification
A. R. Deepa & W. R. Sam Emmanuel [82]	Backpropagation algorithm with Firefly optimization	Combined Feature Classification using an adaptive firefly backpropagation neural network	High error rate and low accuracy for the backpropagation model	BRATS 2015 dataset
Javeria Aminrt et al. [83]	Random forest (RF) classifier using ML techniques	Gabor Wavelet Characteristics, Local Binary Patterns, some of the features include segmentation-based fractal texture analysis and scatter plot of oriented gradients.	Many old feature extraction and segmentation methods are introduced that produce low accuracy.	BRATS 2012, 2013 and 2014 datasets.
McKinley et al. [84]	CNN	Dense net is a semantic segmentation algorithm that replaces pooling with dilated convolutions	In dense layer data dropout problem	2017 BRATS challenge
Aparna Natarajan et. al. [85]	Resourceful Separation of Brain Tumor Using fast learning technique	CNN PNN and DNN	Low accuracy when evaluated with default optimizers	MRI images dataset
Ben naceur, M. et. al. [86]0	Recognition of brain growths using deep approach-based CNN	DCNN (Dense-MultiOCM)	Conventional preprocessing and noise removal techniques are used for real-time data	BRATS-2018 dataset
Amiri, S. et. al. [87]	Structure RF and Bayesian network for brain tumor classification	RF, ANN, and CNN	The Cross trained module does not work for the heterogamous classifier.	Brain Tumor Image Segmentation Challenge (BRATS, 2015) dataset

methodologies. In this section, we will go through various challenging datasets that are both significant and crucial. The BRATS datasets are considered to be the most difficult MRI datasets [73], [74], [75]. BRATS Challenge is issued at different times throughout the years, and more recent challenges have had a resolution of 1 mm3 voxel [76]. Employed two benchmark datasets and one dataset obtained from qualified radiologists. These datasets include 15 photographs of patients, and each patient included 9 slices of imaging data. The core dataset that was used was known as the digital imaging and communication in medicine (DICOM) dataset. Twenty-two photos from the DICOM collection, some of which depict tumor-infected brain tissue, have been taken into consideration for the purpose of this investigation. This dataset did not contain any images that represented the ground truth. The brain web dataset [77] was used as a supplemental source of information for this study. The whole three-dimensional simulated brain MR data that is included in this paper were obtained using three modalities: proton density-weighted MRI, T1, and T2-weighted MRI, and T1-weighted MRI. The BRATS 2017 dataset [78] was utilized by Shubhashis Banerjee and Francesco Masulli. This dataset comprises data from the BRATS 2012/13/14, and 2015. A total of 210 HGG cases and 75 LGG instances of brain tumors are included in the dataset. The patient's MRI scan includes four distinct MRI sequences: the initial (T1) sequence, the T1 & T2 weighted sequence, and the Fluid Attenuated Inversion Recovery (FLAIR) volume with 155 two-dimensional slices at a resolution of 240 by 240. The BRATS training dataset, which consists of 274 multi-modality MRI images of people with gliomas, is used by the researchers Ali Isin, Cem Direkoglu, and Melike sah (both high and low grades). For the purposes of testing, a total of 110 scans were taken from ground truths and unknown grades.

B. TUMOR CLASSIFICATION APPROACHES

The input data is sorted using classification techniques into a variety of separate classes., after which training and validation are carried out using both known and unknown instances. The classification of tumors into relevant classifications is a widespread application of machine learning, tumor as well as non-tumor, and malignant and benign tumors. Supervised methods include KNN, support vector machine, nearest subspace classification model, and representation classification model. Fuzzy C Means, hidden Markova random field, and self-organization map, are examples of unsupervised approaches [67], [68], [69], [70], [71].

C. DL MODELS

Deep learning (DL) models, as opposed to shallow Machine Learning (ML) techniques, are founded on the principles of learning data representations as well as learning hierarchical features. Deep learning techniques are used to categorize brain tumors, and these techniques find the descriptive data that most properly describes the many forms of brain tumors. The classification of brain tumors shifts away from being driven by manually created characteristics and toward being driven by data due to the nature of deep learning [87]. In the domain of deep learning technics, a convolutional neural network is one of the most popularly utilized ones for the categorization of brain tumors, and a significant amount of progress has been made [88]. There are a few different

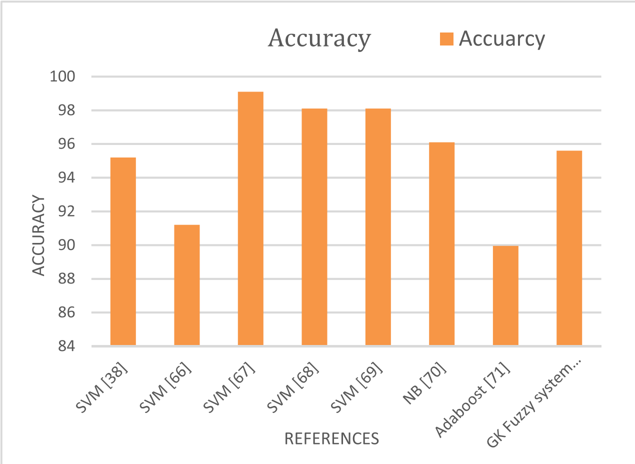

FIGURE 1. Evaluation of machine learning techniques for brain tumor detection.

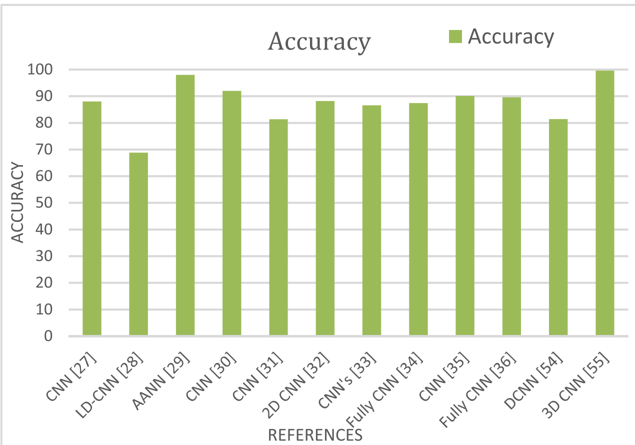

FIGURE 2. Evaluation of deep learning methods for brain tumor detection.

approaches that may be taken when classifying brain tumors, which can be seen in the research that was looked through. The difference includes the following aspects: (i) the dataset that was used for categorization, which included the types of tumors; (ii) the pre-processing as well as data augmentation methods that were incorporated; (iii) The use of ROI segmentation as a preliminary step in classification; The use of either a pre-trained or custom-designed deep learning technique; and (iv) the ROI segmentation question. For example, Bada and Barjaktarovi'c [88] used contrast-enhanced T1-weighted brain tumor MRI images that were readily available to the public [89]. Meningioma, glioma, and pituitary tumor scans are included in the collection, as well as images from the three anatomical perspectives of axial, sagittal, and coronal. The images were preprocessed using several techniques, such as scaling and normalization, among others. To increase the size of the training dataset, the photographs in the dataset are also flipped vertically and rotated via a 90-degree angle. Additionally, they employed a specially

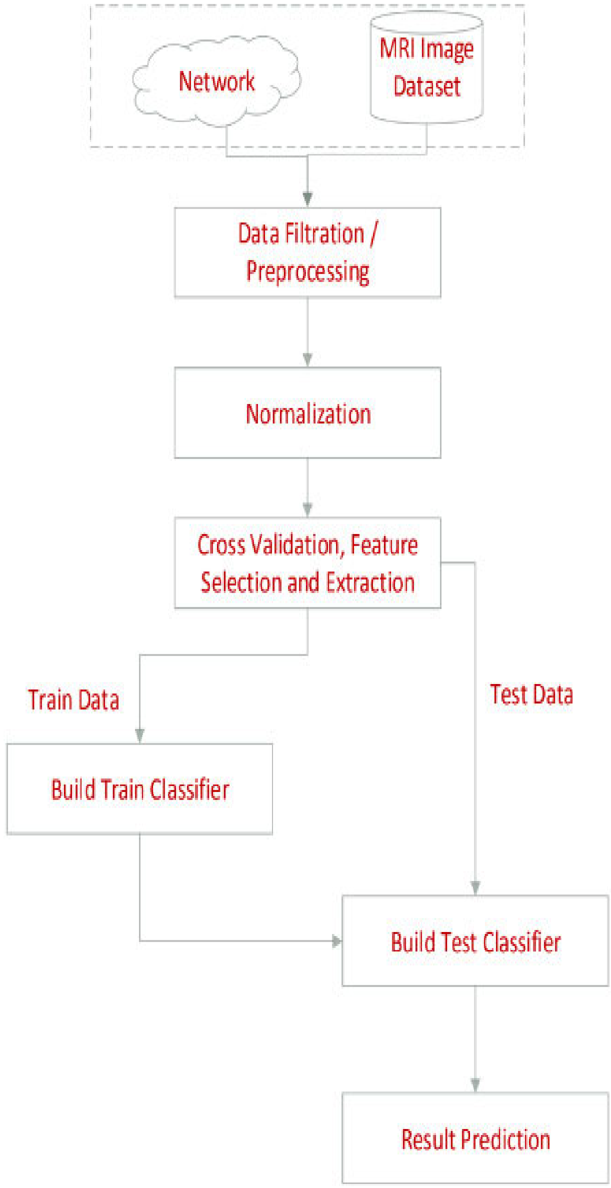

FIGURE 3. Flowchart of the proposed work.

created CNN classifier trained with the Adam optimizer using a mini-batch size of 16 and then tested the Classifier with 10-fold cross-validation. A Glorot initializer is used to get the convolution layers' weights started off in the right direction. The measures utilized to assess the model's performance were the highly sensitive, selectivity, accuracy, recall, and F1-score. Meningiomas, gliomas, and pituitary tumors all have sensitivity values of 89.8%, 96.2 percent, and 98.4%, respectively. Meningiomas have a specificity of 90.2 percent, gliomas have a specificity of 95.5 percent, and pituitary tumors have a specificity of 97.7 percent according to the model. In addition, the models have an overall accuracy of 95.4 percent, an average precision of 94.81 percent, an average recall of 95.07 percent, and an F1-score of 94.94 percent, correspondingly. Convolutional neural networks, Deep CNN, dual-force CNN, cascaded CNN, 3-dimensional CNN, and Modern deep learning techniques are employed to train the data in the healthcare sector, including convolutional encoder networks, long short-term memories, CRF, U-Net CNN, and WRN-PPNet [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62].

D. PARAMETERS

MRI images are identified and categorized using an automated technique, as described in [31]. The Super Pixel Methodology forms the foundation for this strategy, as does the categorization of every Super-the pixel. When attempting to categorize each superpixel as either tumorous or normal; the extremely randomized trees classification model is evaluated alongside the support vector machine. This methodology utilizes two datasets, which are referred to as a dataset of BRATS released in 2012 and 19 MRI FLAIR images respectively. The findings indicate that the utilization of the ERT classifier yields satisfactory results for this strategy. An instinctive organization technique is employed to recognize a tumor using a convolutional neural network with 3 × 3 tiny kernels [84]. The tumor is ordered using this technique. The method won the BRATS Challenge in 2013 by simultaneously placing first in the whole, core, and improving areas of the dice similarity, coefficient metric (0.880, 0.830, and 0.770). In the [32], the Alexnet model convolutional neural network is rummage-sale to concurrently identify multiple sclerosis and normal tumors. A convolutional neural network was successful in correctly categorizing 98.67% of the photos into one of three categories. To segment brain cancers from MRI scans, a multi-stage Clustering framework was proposed in [54]. According to [85], there is a method for categorization and segmentation that makes use of CNNs that is both efficient and effective. Image-Net was utilized in the suggested method in order to extract features. According to the findings, the classification was accurate to the extent of 97.5%, while the segmentation was accurate to the extent of 84%. In the study referred to as [86], Analysis of multiphase MRI images for tumor grading has been conducted, and the results of base neural networks and deep learning structures have been contrasted and compared. According to the findings, the performance of the network which is measured by the specificity and sensitivity of CNN has increased by 18 percent when related to the efficiency of neural networks. In the paper [33], the authors present a deep learning-based supervised technique for detection variations in artificial opening radar scans. This technique provides a dataset that had an adequate amount of data volume and variety for the purpose of training the DBN with the help of the input photographs and the images that were acquired by applying structural operatives on those images. The finding accuracy of this technique demonstrates the applicability of techniques based on deep learning for the purpose of finding solutions to change detection challenges.

E. LIMITATIONS OF ML OVER DL APPROACHES

Recent research on the diagnosis of brain tumors is examined in this survey; the findings suggest that there is an opportunity for further development in this area. Noise is introduced into an MRI scan during the image capture process, and removing this noise is a complex process [20], [21], [22], [23]. Due to the tentacles and dispersed features that are characteristic of brain tumors [23], [24], [25], accurate segmentation is a thought-provoking task. In order to achieve better categorization, one of the most significant tasks is to select and retrieve the optimal features, as well as determine the right amount of training and testing samples [26], [27]. The fact that deep learning models can autonomously learn new features is one of the reasons they are getting popular. On the other hand, these models need a portion of memory and a lot of dispensation control. Therefore, it is still necessary to develop a lightweight computing framework that can produce a high ACC in a shorter length of time. The following is a list of the primary difficulties associated with detecting brain tumors. The glioma tumor and the stroke tumor do not contrast very well with one another. It is made up of tentacles and scattered components, both of which make the segmentation and categorization procedures far more difficult [83]. The identification of a tiny volume of the tumor remains difficult since it is possible for it to be recognized as a normal area [29]. Some of the existing approaches perform admirably for a complete tumor region but not for other regions (whether enhanced or not), and conversely [90], [91], [92], [93], [94], [95].

F. FUTURE RESEARCH DIRECTIONS

This survey includes all of the significant features as well as the most recent work that has been done along with their constraints and obstacles. The researchers will benefit from gaining a better understanding of how to do new research in the appropriate manner within a reasonable amount of time. Even though deep learning approaches have made substantial contributions, there is still a need for a generic approach. These methodologies produce better outcomes once training and testing are carried out on achievement features (intensity range as well as resolution) that are comparable; moreover, the robustness of the methodologies are directly impacted by even the slightest change between the training imaginings and the testing imaginings. In the future, studies may be conducted to detect brain cancers more precisely, with actual patient information since somewhat average (various image capture methods) (scanners). Combining handcrafted characteristics with deep features has the potential to enhance classification accuracy. Similar to this, lightweight technologies like quantum machine learning are crucial in enhancing accuracy and efficacy, which in turn cuts down on the time required by radiologists and raises the percentage of patients who survive their illnesses. An attention-based mechanism improves brain tumor segmentation outcomes and reduces computational complexity issues. To be more precise, an image processing and attention mechanism are used to extract the desired area of the image, and then a pre-trained encoder part extracts the fewest but most crucial features to further improve the efficiency of the results. One of the most studied ideas in the field of deep learning is attention, which is used to solve issues like neural machine translation and image captioning. The attention mechanism idea is supported by a number of theories, including Seq2Seq models, encoders, decoders, hidden states, context vectors, and others. Channel attention, Spatial attention, and Block attention are some of the useful methods.

Some of the suggestions and possible improvements made by the published review articles includes: Further practice of hybrid-based learning technique is important to obtain strong CAD system [88], Noise estimation is challenging in machine learning and in deep learning lack of interpretability [89], How effectively automatic methods can manage the impact of treatment effects is still being researched [90], Technical issues stemming from the difficulty in defining exactly what deep learning is due to the lack of mathematical and theoretical foundations for many of its core models and techniques [91], Research should carefully consider how to lessen or compensate for observer, spectrum, and selection biases, as well as how to increase reporting transparency [92], Research should focus on optimization technique which will decide number of layers and filters in the model [93], Semi supervised training gives weak performance [94], Absences of transfer learning mechanism leads to weak generalization ability [95], Deficiency of training data and no resolution gives poor performance of CNN [96], With large volume of data quality of image segmentation needed to improved [97], Transfer learning model is required incapacitating overfitting of image [98], Accurate analysis is difficult for vast number of images [99], and Computation is difficult with multiple task [100].

IV. PROPOSED FUTURE WORK

The flowchart for the proposed work is given in Figure 3. This describes the execution of the proposed system in the detection of various diseases using CNN. The entire architecture depicts how the system deals with the recognition and detection of the test image, and below we explain the process of execution. The purpose of this research is to combine feature selection approaches with machine learning to identify pre-illnesses. For the early diagnosis of early diseases in MRI, CT scan, and X-ray images, this system makes use of deep learning techniques and image processing technology. to make feature extraction more efficient, the dataset including defective images from several categories was pre-processed and segmented.

Image Acquisition: In image acquisition, heterogeneous images of the medical dataset collected which contains abnormal and normal samples are gathered from a variety of individuals and converted into image format using a camera or some synthetic dataset.

Pre-processing: There may be difficulties like noise, image blurring, and other concerns since the input data samples were gathered from a range of people. As a consequence, pre-processing methods are used for images in order to reduce noise and improve image quality using modern techniques.

Processing the image is tough due to the fact that it is originally in RGB color format. The RGB to greyscale conversion is required to reduce the complexity of a 3D pixel value to a 1D value. Many applications, such as edge detection, do not benefit from the use of three-dimensional pixels.

Feature Selection: In image processing and data mining, feature selection is critical. It calculates the best subset of predicted characteristics from the original data. A subset of the original characteristics is chosen that retains enough information to distinguish successfully across classes. For feature selection, many search techniques can be utilized such as IG, PCA, and RAE.

Feature Extraction: There are six separate sets of photos taken, from various available datasets. The obtained images are then subjected to image processing methods in order to identify valuable information for future study. Because the gathered photos are of various sizes, it is necessary to transform them to a consistent size for effective preprocessing. The RGB photos are first scaled and transformed to Hue Saturation Intensity (HSI) format. Color perception is greatly aided by the use of HSI color space representation. Masking is then used to eliminate the pixels. Setting the pixel value of a picture to zero or another background value is known as masking. The diseased section of the original picture is then segmented using the K-means segmentation technique. The goal of segmentation is to transform a picture's representation into a meaningful image that is simpler to explore. The best characteristics from this dataset are then selected for accurate categorization via feature selection. Relief-f Attribute Evaluator (RAE), Principal Component Analysis (PCA), as well as Information Gain (IG), are the three techniques of feature selection used in this study.

Classification and Recognition: Disease classification is the process of recognizing a test sample and giving it the appropriate class label. The result of the feature extraction module is to feed the classifier as an input. The classifier will identify the right class label for the input image based on the retrieved characteristics. There are a variety of methods for categorization. Deep learning is one of them. Deep learning employs a variety of artificial neural networks, including CNN, ANN, RNN, and others. The image is sent into CNN, which extracts the most important characteristics as distinct layers. The key benefit of the convolutional neural network is that it lowers the amount of work required by humans to extract characteristics.

Implementation Process

1) The images from the dataset can be pre-processed in this phase to prepare the data for subsequent processing. Initially, photos are processed to reduce noise. The photos were then transformed to grayscale and scaled to proper pixels while keeping the aspect ratio constant.

2) The aspect ratio of the picture, the amount of lateral and vertical lines in the picture, the location and number of loops and curves, and other geometrical elements can all be extracted from each image sample through processing. These traits were then combined with the pixel-based information from the image to yield accurate classification outcomes.

3) The input values of a traditional neural network are modified by passing through a sequence of hidden layers. A group of neurons makes up each layer, each of which is totally linked to every neuron in the layer preceding it. The superior performance of CNNs is due to the fact that these networks capture the fundamental features of pictures. This important property of CNN gives the confidence to apply it in the suggested dataset analysis.

4) Download the dataset from open-source websites such as the Kaggle dataset or any unseen dataset.

5) Extract various features by using the CNN model, train module, and save features in a. pkl file. There are below layered concepts in Convolutional Neural Networks:

6) In the dense layer, it will classify the validation image set and show classification results accordingly.

V. CONCLUSION

CAD systems for the detection of brain tumors are developed using brain MRI scans and digital image processing methods like pre-processing, separation, and classification. The classic deep and machine-learning techniques for brain tumor identification are discussed in this work. Various research publications from reputable journals and conferences have been examined, with a full analysis of each work offered. This section provides a summary of commonly used MRI datasets. Although several ML and deep learning methods are used for classification, CNN has shown to be quite accurate. CNN is often used to categorize brain tumors into two types: normal and pathological. The development of an autonomous brain tumor detection system must consider reliability, accuracy, and calculation time. This review examines current methodologies and can be utilized in the future to build effective diagnostic tools for additional brain illnesses that as Alzheimer's disease, Parkinson's disease, dementia, and stroke using various MRI imaging modalities. Implementing this system in collaboration with multiple deep learning algorithms as deep hybrid learning for brain tumor detection and classification will be future work for this study.

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SHUBHANGI SOLANKI received the B.E. degree in computer science from Savitribai Phule Pune University (SPPU), in 2002, and the M.Tech. degree (Hons.) in artificial intelligence from RGPV, Bhopal, in 2007. She is currently pursuing the Ph.D. from LNCT University Bhopal. She has published more than ten paper in journal and conferences.

UDAY PRATAP SINGH (Member, IEEE) received the B.Sc. degree from Dr. Rammanohar Lohia Avadh University, Faizabad, Uttar Pradesh, India, the M.Sc. degree from the Indian Institute of Technology, Guwahati, India, and the Ph.D. degree in computer science from Barkatullah University, Bhopal. He had worked in various areas, such as soft computing, theoretical computer science, and image processing. He is currently working as an Associate Professor with the Department of Mathematics, Shri Mata Vaishno Devi University, Katra, India. He had authored several research papers, published in reputed journals and conferences. He is a Life Member of IAENG and the Computer Society of India.

SIDDHARTH SINGH CHOUHAN received the B.E. and M.Tech. degrees in computer science and engineering from Rajiv Gandhi Proudyogiki Vishwavidyalaya University, Bhopal, India, in 2010 and 2013, respectively, and the Ph.D. degree in computer science and engineering from Shri Mata Vaishno Devi University, Katra, India. He is currently a Postdoctoral with the University of Malta, Europe. He is currently working as an Assistant Professor in SCSE with VIT Bhopal University. He had authored several research papers, published in reputed journals and conferences. His research interests include developing soft computing, computer vision, drone technology, deep learning, and precision agriculture.

SANJEEV JAIN (Member, IEEE) was born in Vidisha, Madhya Pradesh, in 1967. He received the master's degree in computer science and engineering from IIT Delhi, New Delhi, India, in 1992, and the Ph.D. degree in computer science and engineering. He has over 35 years of experience in teaching and research. He is currently the Vice Chancellor with the Central University of Jammu. He has the credit of making a significant contribution to research and development in the area of image processing and mobile ad hoc networks. He has guided Ph.D. scholars and has undertaken a number of major research and development projects sponsored by the government and private agencies. He is a member of various societies, such as the Computer Society of India.