A Deep Survey on Brain Tumour Detection and Classification Using Machine Learning & Deep Learning Techniques

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Abstract:
The World Health Organisation (WHO) identifies brain tumours as one of the leading causes of death in the world. This disease is challenging to identify because of its complexity and cunning character. Because of the high risk of clinical occurrences, persistent brain tumour illness is a severe public health issue worldwide. Despite the general consensus that persistent brain tumour disease has considerable interactions with elevated risks of vascular events, end-stage excretory organ disease, and all-cause mortality, there is still inadequate information on individuals. Deep learning (DL), a branch of machine learning, has recently shown impressive results, particularly in tasks like classification and segmentation. Imaging can be done in various ways to look for brain tumours. Magnetic Resonance Imaging MRI is widely utilized because it produces high-quality images without harmful ionizing radiation. MRI enables the early diagnosis and evaluation of brain tumours as a preventive medical measure. Brain tumour diagnosis is aided by MRI, which provides thorough information on human-sensitive tissue.

The Convolutional Neural Network (CNN) is a popularly used method and sought-after model for classification in modern times. Like the human brain, the CNN-based expert system's input, neurons, hidden layers, and output are all interconnected. The study focuses on developing and optimizing deep learning models to handle the complexity and heterogeneity of brain tumours. CNNs are commonly employed for their ability to automatically learn discriminative features from medical images, particularly MRI scans. These models leverage large datasets to understand representations that capture the subtle variations and distinctive patterns indicative of brain tumours.
Keywords: Brain tumour, Deep Learning, Machine Learning, Convolution Neural Networks (CNN), MRI
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1. Introduction

An abnormal multiplication of brain cells is referred to as a "brain tumour". There are both primary and secondary brain tumours. While secondary tumours begin in several parts of the body, such the skin, lungs, and intestines, before travelling to the brain, primary tumours begin in the rain. Glioma, pituitary, and meningioma are the three subtypes of tumours based on the cells that give rise to them.

A brain tumour is an abnormal growth of cells within the brain or its surrounding structures. It is a type of tumour that originates in the brain, rather than spreading to the brain from another part of the body (which would be called a metastatic brain tumour). Brain tumours can be benign (non-cancerous) or malignant (cancerous). Benign brain tumours grow slowly and have distinct boundaries, meaning they do not invade nearby tissues. They are generally less life-threatening than malignant tumours and may not require immediate treatment unless they cause significant symptoms or affect important brain functions. Malignant brain tumours, on the other hand, are cancerous and tend to grow more rapidly. They have the potential to invade nearby healthy brain tissue and can expand to other central nervous system regions. Malignant brain tumours can be broken down even further into subcategories depending on the cell type from which they arose, such as gliomas, meningiomas, or metastatic tumours[23,26].

The exact causes of brain tumours are not always known, but certain factors may increase the risk, such as exposure to ionizing radiation, a family history of brain tumours, certain genetic syndromes, and rarely, exposure to certain chemicals or environmental factors. The symptoms of brain tumours can vary depending on their size, location, and rate of growth. Common symptoms include persistent headaches, seizures, changes in vision or hearing, difficulty speaking or comprehending, weakness or paralysis, problems with balance or coordination, and personality or mood changes.

Diagnosis typically involves a combination of imaging tests such as MRI or computed tomography (CT) scans, and in some cases, a biopsy may be performed to obtain a sample of the tumour for further analysis. Figure.1 shows the MRI scans of brain tumours.

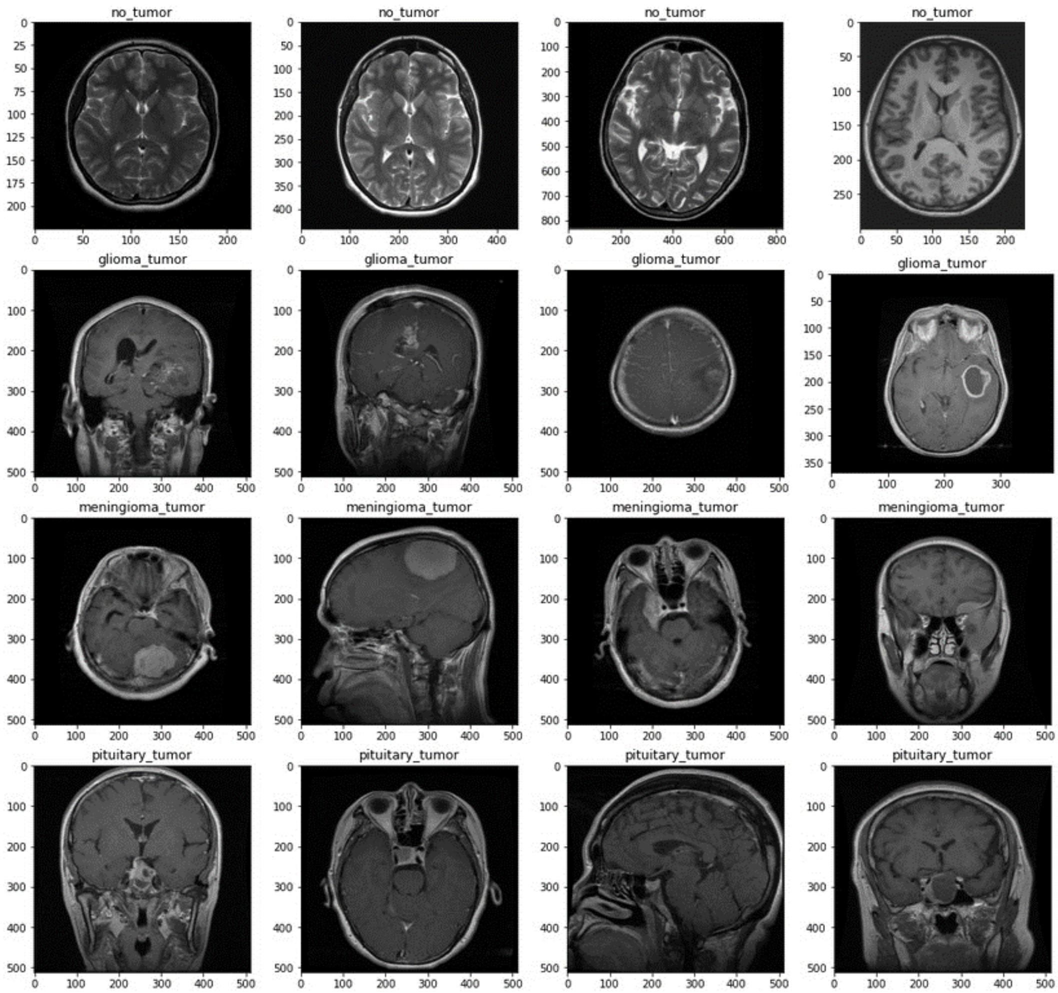

Figure. 1

The prognosis for a patient with a brain tumour is contingent on many factors, such as the nature of the tumour, its size and location, and the patient's general health. Treatment may involve surgery to remove the tumour, radiation therapy, chemotherapy, targeted drug therapy, or a combination of these approaches [12].

It's important to note that brain tumours can be a complex and serious condition, and treatment outcomes can vary widely depending on individual circumstances. Consulting with a medical professional and a neuro-oncologist is crucial for accurate diagnosis, treatment planning, and ongoing management [18].

2. Literature survey:

Recent years have seen a lot of research focused on modifying deep learning models to diagnose brain tumours. Deep learning plays a significant role in detecting and classifying brain tumours by leveraging its ability to analyse large amounts of medical imaging data and extract meaningful patterns and features [1]. Here are some key aspects of deep learning in this context:
Image Segmentation: Deep learning models can segment brain images to identify and outline the tumour region. This process helps in accurately localizing the tumour and distinguishing it from healthy brain tissue [3]. CNNs a popular deep learning architecture, are commonly used for image segmentation tasks.

Tumour Detection: Deep learning models can be trained to detect the presence of brain tumours in medical images. By learning from vast datasets of labelled images, these models can automatically identify abnormalities and highlight potential tumour regions. CNNs are often employed for tumour detection [3], where they learn to recognize distinct tumour characteristics.

Classification: Deep learning models can classify brain tumours into different types based on their characteristics. By training on annotated datasets, these models can learn to differentiate between different tumour types, such as gliomas, meningiomas, or metastatic tumours. CNNs, recurrent neural networks (RNNs)[5], or hybrid architectures can be used for classification tasks.
Feature Extraction: Deep learning models excel at automatically learning and extracting relevant features from medical images. By analysing the intricate patterns and subtle details in brain scans, deep learning models can uncover features that may be indicative of specific tumour types or characteristics [15]. These learned features can assist in accurate diagnosis and treatment planning.

Improving Diagnostic Accuracy: Deep learning models can help radiologists and clinicians improve their diagnostic accuracy by providing them with computer-aided assistance. By analysing brain images and generating predictions, these models can aid in detecting subtle abnormalities that may be missed by human observers alone [6]. This can lead to earlier detection and improved patient outcomes.

Large-Scale Data Analysis: Deep learning models excel in handling large-scale datasets, making them well-suited for analysing extensive collections of medical images [9]. By leveraging these datasets, deep learning models can learn from a diverse range of tumour cases, leading to improved generalization and robustness in tumour detection and classification.

Personalized Medicine: Deep learning models can contribute to the development of personalized treatment strategies for brain tumour patients. By analysing various imaging modalities, genomic data, and clinical information, deep learning models can assist in predicting treatment response, recurrence risk, and patient outcomes [8]. This can aid in tailoring individualized treatment plans and optimizing patient care.

Automation and Efficiency: Deep learning-based systems can automate the tumour detection and classification process, reducing the manual effort and time required by radiologists and clinicians. This automation can lead to more efficient diagnosis and treatment planning [10], enabling medical professionals to focus on other critical aspects of patient care.

Integration with Healthcare Systems: Deep learning models can be integrated into existing healthcare systems and picture archiving and communication systems (PACS) used in radiology departments. This allows for seamless integration of the deep learning algorithms into the clinical workflow, facilitating easy access to the models and their predictions during the interpretation of medical images.

Continuous Learning and Improvement: DL models have the capability to continuously learn and improve their performance over time. By leveraging feedback from radiologists and clinicians, these models can adapt and refine their predictions, leading to iterative improvements in accuracy and reliability [32].

Here are a few commonly used deep learning algorithms that have shown effectiveness in this domain:

Convolutional Neural Networks (CNNs): CNNs have been widely used for image-related tasks, including brain tumour detection and segmentation. Their ability to learn hierarchical representations and spatial relationships in images makes them well-suited for analysing medical imaging data [29].

Recurrent Neural Networks (RNNs): RNNs, particularly variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), are commonly used for sequence analysis tasks. In the context of brain tumour classification, RNNs can be utilized for processing sequential data such as time-series information or sequences of medical imaging slices.

3D Convolutional Neural Networks: Traditional CNNs operate on 2D image slices, but for volumetric medical imaging data such as 3D MRI or CT scans, 3D CNNs can be more effective. By considering spatial information across multiple slices, 3D CNNs can capture 3D structural details and improve accuracy in tumour detection and classification[31].

Transfer Learning: It involves using pre-trained models trained on large-scale datasets (e.g., ImageNet) and adapting them to specific tasks. This approach can be effective when labelled brain tumour datasets are limited. By leveraging the pre-trained knowledge, transfer learning can boost the performance of deep learning models in brain tumour detection and classification tasks[32].

Generative Adversarial Networks (GANs): GANs can be utilized for tasks like generating synthetic brain tumour images or augmenting the available datasets. GANs can learn the underlying distribution of tumour images and generate realistic synthetic samples, which can be used to improve the robustness and generalization of deep learning models [45].

3. Understanding different DL & ML Approaches for BTD:

It's important to note that the success of a deep learning algorithm depends not only on the algorithm itself but also on data quality, proper preprocessing techniques, model architecture, hyperparameter tuning, and domain expertise [45]. It is often necessary to experiment with different approaches, evaluate their performance, and fine-tune the models to achieve the best results for a specific task. We have gone through various works and literature survey of different implemented models and observed their accuracies in implementing, detection and classification of brain tumours. Table 1 indicates observations made on brain tumour detection (BTD) using different ways of deep learning techniques. Table.2 indicates observations made on BTD using different ways of machine learning techniques [26].

In this study we have observed different works and made observations on lapses and identified research GAPS from other works. In the following table 1 and table 2 will give complete picture of the research works till date. In contrast to traditional feature extractor methods, CNN does not require any segmentation beforehand. Several researchers have proposed CNN designs. Multiclass brain tumour identification was reported by the majority of CNN models, with a plethora of images. For example, Sultan et al., suggested a CNN model with 16 layers [30]. The majority of the CNN models, using a large pool of image data, reported multiclass detection of brain tumours. Tumours were classified in one dataset as meningioma, glioma, or pituitary tumours, whereas in the other, Grade II, Grade III, and Grade IV gliomas were distinguished. On datasets including 3064 and 516 photos, respectively, they attained 96.1% and 98.7% prediction accuracies. Studies have shown that MR imaging is superior to other modalities for the detection of metastases.

Gliomas are the most common type of brain tumour in adults and can be detected and measured using a variety of MRI sequences, including T2-weighted fluid-attenuated inversion recovery (Flair), T1-weighted, T1-weighted contrast-enhanced, and T2-weighted [45]. Figure 2. Shows the high-grade tumour is highlighted in four distinct ways across the MRI scan. T1, T1-Gd, T2, and FLAIR (from left to right)

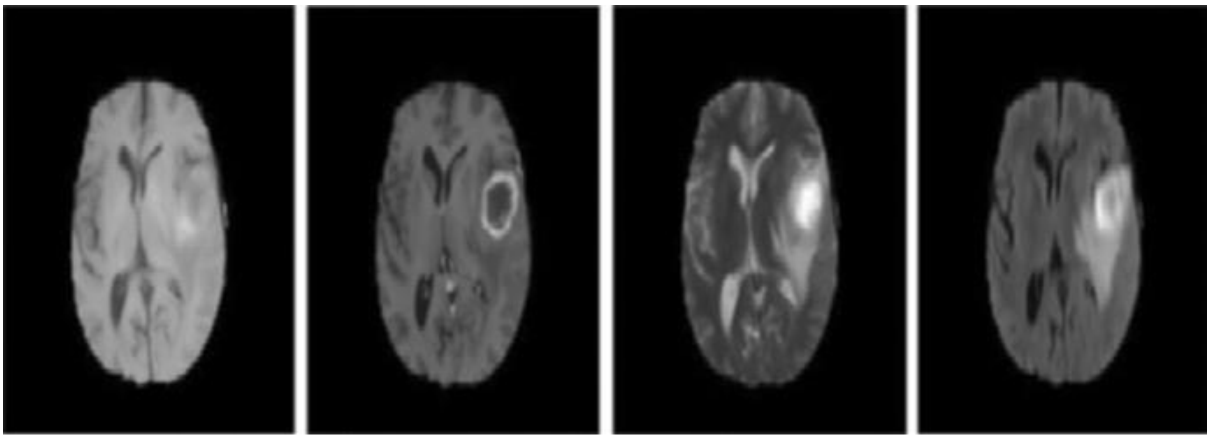

Figure.2

Reference	Methodology	Algorithms	Accuracy
Yota Ishikawaet et al. [18]	Deep CNN, PNN and PNN	Binarization algorithm with water shade feature extraction model	98.50%
Heba Mohsen et al. [19]	Deep Neural Network (DNN)	PCA and DWT classification	96.90%
Justin S. Paul et al. [20]	Numerous Deep learning techniques and Machine learning techniques	CNN	91.40%
Yan Xu et al. [21]	Deep CNN with various Instigation Structures	Various deep learning frameworks for features extraction and classification	97.50%
Kaoutar B. Ahmed et al. [22]	Deep Convolutional Neural Networks (DCNNs)	Fine-Tuning	81.00%
Renhao Liu et al. [24]	DCNN	Detail feature classification of brain tumor Magnetic Resonance	95.40%
Nøhr Ladefoged et al. [25]	CNN	RESOLUTE and DeepUTE	67.105
Himar Fabelo et al. [26]	2D CNN	Multi-layer CNN	80.30%
Yuexiang Li & Linlin Shen [27]	CNN	Multi-view DNN	88.00%
Lina Chato & Shahram Latifi [28]	Normal discriminant analysis	SVM, KNN, LR, and different learning algorithms.	68.80%

Geena Kim [32]	2D Fully CNN	CNN Architecture	88.20%
Parnian Afshar et al. [33]	Feature extraction with DCNN	Capsule Networks (Caps Nets)	86.56%
Peter D. Chang [34]	Feed Forward Neural Network	Fully connected CNN	87.40%
Fabian Isensee et al. [35]	DCNN	U-Net Architecture	90.10%
Sanjay Kumar et al. [36]	Deep-CNN	UNET Architecture	89.60%
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%
Ramin Ranjbarzadeh et. Al [43]	Brain tumor segmentation using deep learning and Attention-based mechanism	Cascade CNN	92.03%
T. Ruba et.al [44]	Brain tumor segmentation using novel LSIS operator from 3D MRI images	Cascaded CNN,3D U-net	-
Aman Verma et al. [45]	Brain tumor classification using deep model	CNN	97.87%
Praveen Kumar Ramtekkar et. al [46]	Brain tumor detection using CNN	CNN	98.9%5
R. Rajasree et al. [47]	Brain tumor classification using deep learning	U-NET, CNN	96.36%

TABLE 1. BTD using DL techniques.

BTD using machine learning techniques involves the application of various algorithms and models to analyse medical images, such as magnetic resonance imaging (MRI) scans, in order to identify the presence and characteristics of brain tumours. We have studied various research work, in which different ML techniques used to BTD and classification of various Tumours [54]. Through these works we come across the present research works and GAPs in the research works. There have been numerous studies and research papers published on the application of ML in BTD [56]. These literature works represent a small sample of the extensive research conducted on machine learning in brain tumours detection. They highlight the progress made in utilizing advanced algorithms and models to improve accuracy and efficiency in the detection and segmentation of brain tumours from medical imaging data [23]. Brain tumour segmentation is important and is usually done by a trained doctor who uses machine learning and deep learning to make decisions [37]. This research summarises a number of high-tech methods for the automatic detection of brain tumours. Data with well-known labels are used in classification techniques to divide the image feature space.

Reference	Methodology	Algorithms	Accuracy
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%
TL. Narayana et al. [66]	Multi-objective genetic heuristic optimizing and SVM on brain MRI images	Segmentation, Feature Extraction, and SVM Classification	91.23%
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%
J. Amin et.al [68]	A computerized brain magnetic resonance approach may distinguish malignant from noncancerous lesions	SVM Classification	98.00%
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%
N. Gupta et.al [70]	Naive Bayes-based decision support system detects and grades tumor severity	Naive Bayes	97.83%
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%

TABLE 2. ML methodologies for BTD.

4. Research gaps identified in ml & dl models from various works:

After observation of different research works of ML and DL on BTD, it is noticed that there are several lapses in identifying BT and its levels. Table 3 summaries the research GAPs identified in al the works [39].

Still, we need to Focus more on 3-D MRI images to identify accurate tumours and its class label. The purpose of the research was to compile a summary of the numerous works of literature that incorporate both technologies for better results, which are shown in Table 3. Common image processing methods used in conventional tumour segmentation techniques include threshold-based approaches [26, 27] and region-based methods [28]. In the case of two-dimensional images, region-based and threshold-based approaches are frequently used [29].

Reference	Methodology	Algorithms	Gap Analysis
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.
Yun Jiang et al. [11]	The Multiscale Convolutional Neural Networks (MSCNN) with Statistical Thresholding	Deep CNN	High communication cost for multiple hidden layers
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.
Muhammad Waqas Nadeem, Mohammed A. Al [13]	Deep CNN has been used for the classification	Deep Learning Methods	Conventional pretrained CNN modules are used.
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.
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.
Heba Mohsen et al. [19]	Deep Neural Network	Principal Components Analysis (PCA) and Discrete Wavelet Transform (DWT)	Low accuracy for both PCA and DWT
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.
Kaoutar B. Ahmed et al. [22]	CNN using the deep learning methodology	Fine-Tuning	High error rate
Mustafa Rashid Ismael [23]	Deep-NNs	Softmax with the Stacked Sparse Autoencoder (SSA)	High-time computation for deep layers
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

Table.3

5. Evaluation of ml & dl approaches:

i) Evaluation of DL techniques for BTD & Its classification:

Evaluation of ML techniques for BTD is crucial to assess their performance and determine their suitability for real-world applications. Figure 3. depicts the accuracy of various ML techniques.

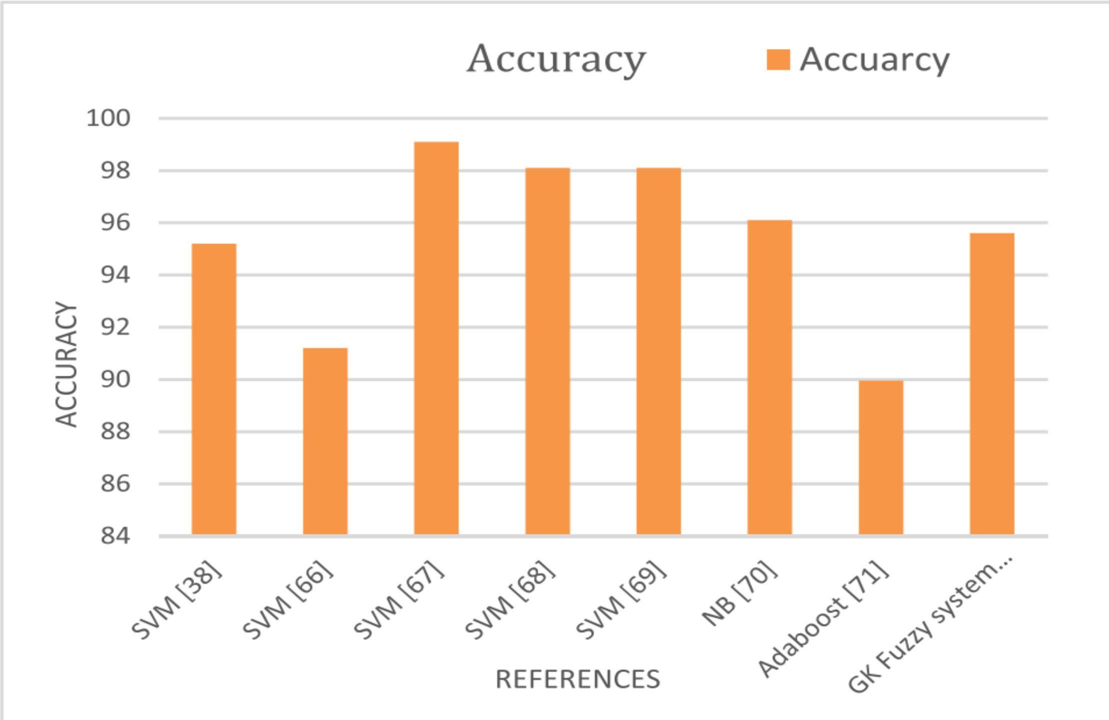

Figure 3. Various Accuracies Using ML

ii) Evaluation of DL techniques for BTD & its classification:

Evaluation of DL techniques for brain tumour detection is crucial to assess their performance and determine their suitability for real-world applications [65]. Figure 4 depicts the accuracy of various DL techniques.

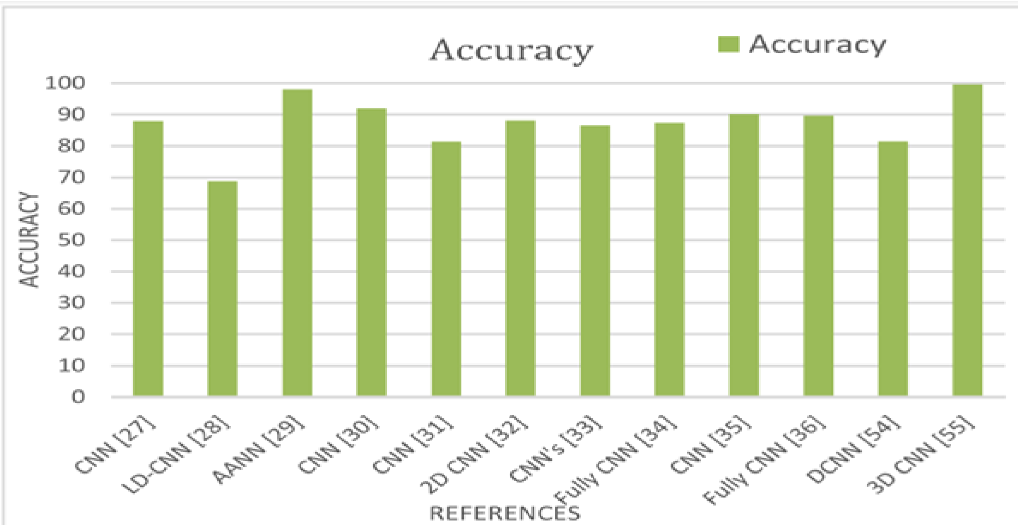

Figure 4. Various Accuracies Using DL

6. General steps involved in any cnn based dl method:

Step 1: Data Collection and Preprocessing

Gather a dataset of brain MRI images, consisting of both tumour and non-tumour cases. Ensure that the dataset is representative of the different tumour types and contains a sufficient number of samples. Preprocess the data, which may involve resizing the images, normalizing pixel intensities, and removing artifacts or noise.

Step 2: Data Splitting

Split the dataset into training, validation, and testing sets. The training set is used to train the model, the validation set is used to tune hyperparameters and assess model performance during training, and the testing set is used to evaluate the final model's performance.

Step 3: Feature Extraction

Extract relevant features from the pre-processed brain MRI images. These features can include intensity, texture, shape, and spatial relationships. Popular feature extraction methods include wavelet transforms, Gabor filters, and histogram of gradients (HOG).

Step 4: Feature Selection (Optional)

Optionally, carry out feature selection in order to lessen the dimensionality of the feature space and enhance the effectiveness of the computational process. Techniques such as correlation analysis, information gain, or L1 regularization can be employed to select the most informative features.

Step 5: Model Selection and Training

Choose a suitable machine learning algorithm for tumour classification, such as support vector machines (SVM), random forests, or neural networks. Train the selected model on the training data using the extracted features. Fine-tune the hyperparameters of the model using the validation set to optimize performance.

Step 6: Model Evaluation

Evaluate the trained model's performance on the testing set to assess its accuracy, sensitivity, specificity, and other relevant metrics. Perform a thorough analysis of the model's performance, including confusion matrices, ROC curves, and precision-recall curves.

Step 7: Model Optimization (Optional)

Depending on the results of the initial evaluation, iterate on the model by fine-tuning hyperparameters, modifying the feature extraction process, or exploring different algorithms to improve performance.

Step 8: Validation and Deployment

Validate the model's performance on external datasets or with the help of domain experts to ensure its generalizability. Once satisfied with the model's performance, deploy it for real-world applications, such as assisting radiologists in tumour classification tasks.

Step 9: Continuous Improvement:

Monitor the model's performance in real-world scenarios and gather feedback to identify areas for improvement. Continuously update and refine the model as new data becomes available or new techniques are developed [33]. Figure 5 is general model for Detection and classification of Brain Tumours using CNN based DL Approach.

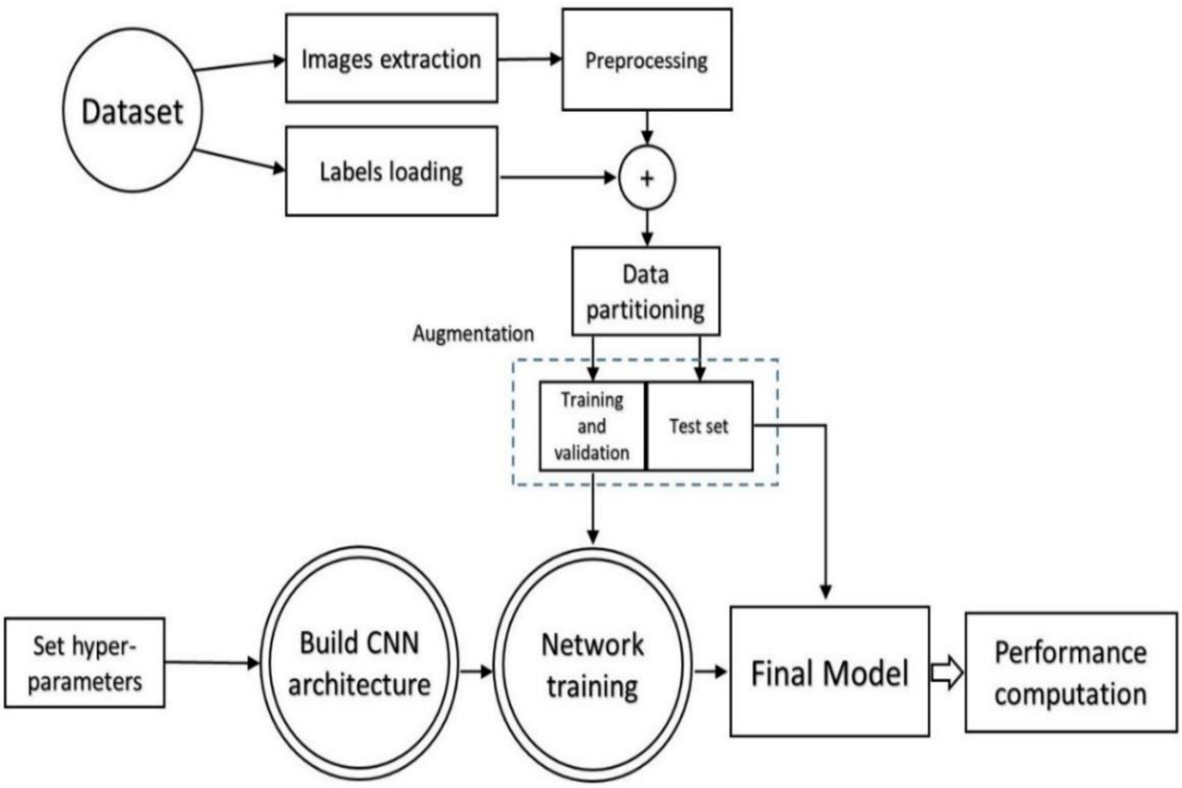

Figure 5. General Model for detection & classification of Brain Tumour

7. Future recommendations:

Three areas will be the most important to improve in the future and require the most attention:

1) The development of CNN as more layers are added to create DCNN.
2) Data improvement and visualisation enhancement.
3) Advance by consolidating more disease prediction expertise into a single expert system.

8. Conclusion:

Digital image processing techniques such as pre-processing, separation, and classification are applied to MRI scans of the brain in order to create approaches for detecting brain tumours. In this paper, we reviewed the state-of-the-art deep learning and machine learning approaches for diagnosing brain tumours. Research articles published in high-quality journals and presented at prominent conferences have been analysed in depth. Although many ML and DL techniques are utilised for classification, CNN has shown to be very effective. CNN is frequently used to distinguish between benign and malignant brain tumours. Reliability, precision, and computation time are three factors that should be taken into account while designing an autonomous brain tumour detection system. When designing an autonomous BTD system, it's important to keep factors like accuracy, calculation time, and reliability in mind. This article takes a look at the present methods that can be used to develop useful diagnostic tools for other brain ailments like Alzheimer's, Parkinson's, dementia, and stroke utilising different MRI imaging modalities in the future.

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