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A Comprehensive Review of Brain Tumor Detection Using Machine Learning and Deep Learning: Challenges, Gaps and Future Directions

Abstract: **-** Patient survival is impacted by the growing prevalence of brain tumor, which makes prompt and precise detection extremely difficult. Machine Learning (ML) and Deep Learning (DL) have become essential for enhancing the identification and categorization of brain tumor due to developments in medical imaging and computational intelligence. This article offers a comprehensive overview of the approaches taken by several researchers to identify brain tumors using ML and DL models. The study points out the shortcomings of the existing approaches, including the need for improved segmentation algorithms, the small dataset size, and the absence of real-time data. In order to fill these gaps, author suggests a hybrid neural network model that reliably localizes tumor and classifies them as benign or malignant by combining Convolutional Neural Networks (CNNs) with sophisticated pre-processing and feature extraction techniques.

Keywords: Brain Tumor Detection, Machine Learning (ML), Deep Learning (DL), Convolutional Neural Networks (CNN), MRI Image Classification

I. Introduction

More than 200 different forms of tumor can affect a person, and they are classified as either benign or malignant neoplasms in medical terminology [1]. The American Cancer Society defines a brain tumour as a dangerous condition that impairs brain function and results in the development of aberrant brain tissue. The National Brain Tumour Foundation (NBTF) reported that within the past three decades, the death rate from brain tumor has risen by 300% [2]. Brain tumor that are not adequately treated may be fatal [3]. The complexity of brain tumor makes it challenging for medical professionals to diagnose and treat people with them. Early detection of brain tumor and the initiation of therapy have a significant impact on these patients' prognosis [4].

The survival rate of these patients is largely dependent on the timely initiation of treatment and the accurate diagnosis of brain tumor [4]. Finding an alternative method to endoscopy that can accurately diagnose the condition is therefore crucial. The most popular and successful technique for identifying brain tumors is nuclear MRI. These tumors are known as benign brain tumor or non-malignant brain growth. As benign brain tumor progress, pressure may be applied to the brain tissue. Another kind of brain tumour is a brain malignancy, sometimes known as a malignant brain tumour. There are three primary kinds of brain tumor gliomas, meningiomas, and pituitary tumors which are further subdivided into subgroups according to their forms and features. Gliomas fall within the category of neoplasms that arise from brain structures other than blood vessels and neurons [5].

An example of normalized MRI scans displaying various tumor kinds in various planes may be found below in figure 1[5]. The pictures display a tumor surrounded by a red border. In every aircraft, there are particular cases of each type of cancer.

Advances in machine learning, especially deep learning, have made it possible to identify and classify patterns in medical imaging.One of the major achievements in this domain is the capacity to access and extract information from records rather than relying on expert knowledge or systematic texts. ML is becoming recognised as a practical method for improving performance across a range of medical applications, such as tissue segmentation, image classification, disease diagnosis and prognosis, and molecular and cellular structure research [6],[7],[8].The most efficient methods for processing images at the moment are CNNs. For massive image input volumes, these multi-layered networks provide great diagnostic precision [9], [10]. Notably, a number of DL and

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ML techniques have been used to diagnose lung tumor, a kind of cancer, and to find cardiovascular stenosis. Additionally, assessments of their talents show that they perform extraordinarily well in diagnostics [11].

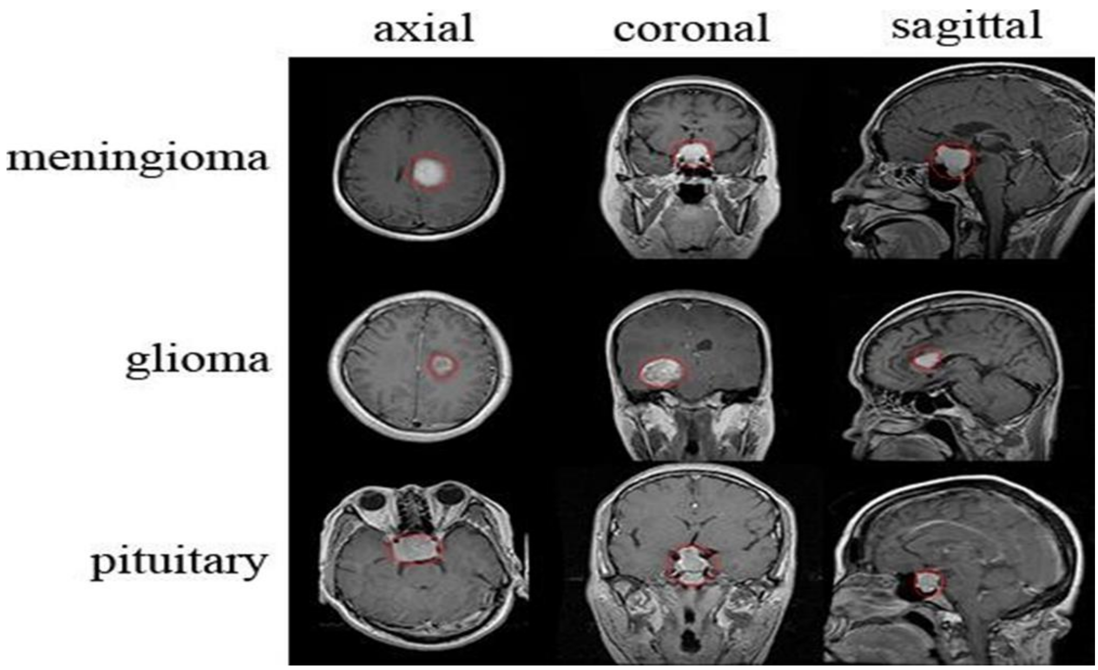

Fig. 1: MRI images showing different types of tumours in different planes [5]

The author of this study reviewed the literature on the identification of brain tumour disorders using a variety of machine learning and deep learning technologies used by other researchers. Additionally, the author examined the gaps in the body of previous work and presented his suggested approaches to get beyond the restrictions. The author finished by summarizing the results of the literature study and outlining the future scope, which will serve as a guide for several aspiring researchers who wish to work in the field of brain tumour sickness. The author of this study reviewed the body of research on brain tumour detection in great detail, emphasizing how different researchers have used machine learning and deep learning technology.

II. LITERATURE REVIEW

Recent years have seen the development of several techniques for categorizing brain tumor based on various standards.

By researching the use of CT and MRI for brain cancer diagnosis, M.M. Khan et al. learnt a lot of fresh information. The author examined how CNNs may be used to diagnose brain cancers from images. It expedites the course of treatment and increases its dependability. To increase accuracy, the proposed model employs a transfer learning technique. This work employed two pre-trained CNN models, VGG19 and MobileNetV2, to excerpt important deep features. The suggested approach yielded 97% accuracy for MobileNetV2, whereas it delivered 91% accuracy for VGG19. As a result, the author can identify tumor before they cause the patient to experience serious symptoms like paralysis [12].

There is broad agreement that CNNs are highly effective methods for analyzing large image collections. In order to make its forecast, CNN shrinks the image without losing any crucial information. Using MRI images of brain tumor, P.G. Brindha et al. developed an ANN model that demonstrated 65.21 percent accuracy in testing. Because of the low accuracy, the author proposed employing a data augmentation approach to add more photos to the collection. Trial and error led to the creation of the proposed model. Optimization techniques can then be used to identify the best possible mix of model layers and filters. When using the currently available dataset, CNNs have demonstrated greater accuracy in making predictions of this type [13].

In order to identify and segment tumor, Sailunaz et al. emphasized brain MRIs in 2D and 3D. A web-based UI for an automated system that can recognize and categories brain tumor with a dice score of 90 or more was created in order to accomplish this aim. CNN models evaluate the inputs to control whether the cancer is there or not, and the system uses image characteristics to detect the tumor. A probability score shows how accurate the forecast was. The U-Net and U-Net++ models may be used to segment tumor on 2D and 3D brain imaging. The segmented tumour, tumour range fraction, and confidence score for the cancer segmentation technique are displayed in the findings. In tumor classification, almost 90% accuracy was achieved [14].

A transfer learning-based strategy utilizing a pre-trained VGG19 model was proposed by S. Sharma et al. Author employed preprocessing techniques including normalization and data augmentation with enhanced CNN planning to improve the proposed model. The proposed model's sensitivity and accuracy were 94.73% and 98%, respectively. The results demonstrated that the suggested model outperformed the most advanced models. There were 257 photos in the training sourced from Kaggle dataset, 100 of which show healthy brain tissue (NT) and 157 of which show BT. Solutions for clinical applications that may identify brain cancers in CT images may now be developed using these models [15].

Deep learning methods have greatly improved cancer classification, with reliable annotations available for public datasets. These methods often include the usage of 3D prototypes that make use of 3D volumetric MRIs or 2D models that handle each slice independently. Nonetheless, the brain tumour can be identified using "socio-spatial" models that consider each altitudinal measurement separately or by viewing the sections as a series of changing pictures. In order to classify and diagnose brain tumor, S. Chatterjee et al. used two spatiotemporal representations: ResNet (2+1) D and ResNet Diverse Complication. ResNet18, a solely 3D convolutional network, was shown to be less successful than both of these models. Furthermore, it was shown that the models' performance was enhanced by pre-training them on an unrelated dataset [16].

T. Zhou et al. suggested a novel technique for locating a brain tumour recurrence in several MR modalities. To make up for the short dataset, the author recommended applying transfer learning. Because the current network has been pre-trained using a bigger training dataset, it is able to abstract ironic semantic features for separation and computation. To combine the several modalities, the author employed a feature synthesis model with multiple channels and numerous scales. The experimental results confirmed that the suggested approach was effective in identifying the site of brain cancer recurrence from the limited information [17].

The proposed study by L. Gaur et al. predicted whether or not an MRI image contains a cancer with 94.64% accuracy using a description-determined double-contribution CNN model. The suggested CNN model was trained and assessed using a set of brain MRI pictures. The SHAP and LIME techniques were then explained using the same model. In order to improve feature extraction, the experiment used two copies of the dataset as input: one at the complication level and the other at the fully related level. Since attempts to exclude characteristics produced a less successful prediction model, no augmentation was carried out. A locally interpreted model with a prototypical-undecided description was suggested in order to provide laypeople a more [18].

According to D. S. Wankhede et al., the pre-processing of the pictures in the dataset involved determining the usual and careless aberration of the concentration principles from each brain MRI scan in each region. Medical picture noise was reduced with the application of a bilateral filter. Tumour segmentation and radiomic characteristics were extracted from the processed medical pictures. As a result, the tumour is automatically divided into four pieces using Clustering (MFCM), which is based on mutually exclusive criteria. Using the rough set notion, the author proposed an alternative method of dimensionality reduction that included a Grey Wolf Optimizer (GWO). The author distinguished between HG and LG GBM utilizing unique feature relationship restrictions [19].

In their study, Karayegen et. al. introduced a semantic separation technique that automatically separates brain tumors from four imaging modalities (T1, T1C, T2, and Flair) in 3D brain cancer segmentation (BraTS) image datasets using a CNN. Additionally, the proposed study used entire brain 3D imaging to compare 3D predicted labels to 3D ground truth labels. It was demonstrated that the axial, coronal, and sagittal planes of the pictures helped precisely determine the tumor's location, height, width, and depth. This strategy was used successfully. Using semantic segmentation carried out by a deep learning network, positive findings for cancer prediction assessments were discovered. The average expected accuracy came out to be 91.71%. The average BF score was 92.93%, while the average IoU score was 86.94% [20].

V.V.S. Sasank et al. developed segmentation based on tumour development models. At one scan point, it absorbs cell density patterns, and at another, it adds textural features. The retrieved characteristics are then divided up using a fully resolved convolutional network (FrCN). The Lattice Boltzmann Method (LBM) may become more complex as a result of parameter selections, even if the cancer development model correctly segments tumor. When used with LBM, hybrid optimization approaches can improve the extraction of intense features. With a clock time of only 0.3504s, the suggested approach is therefore faster than the existing modelling techniques. The segmentation's precision keeps becoming better. The BRATS 2020, 2019, and 2018 datasets were used to evaluate the planned segmentation strategy [21].

For predicting the separation of brain tumor over time, L. Pei et al. proposed two methods: a feature fusion-based method and a JLF strategy. The approach based on feature fusion combines tumour cell density patterns with stochastic texture structures in an RF-based separation strategy to improve surface-centered brain cancer separation in longitudinal MRI. In terms of processing speed and tumour classification accuracy, the suggested feature fusion strategy outperformed earlier techniques. The JLF-based method combines the results of Random Forest with Boosted Galima (GB) to boost GB's dependability as the accepted benchmark for longitudinal brain tumor segmentation [22].

A. Elazab et al. created GP-GAN, a revolutionary data-driven technique, which uses organized 3D GANs, to forecast the trajectory of malignant tumor. The author employed a novel stacked conditional GAN with L1 and dice losses in the objective function. Furthermore, the author guided the generator via partitioned feature maps, which resulted in a higher-quality output. Adding hierarchical characteristics to the produced photos will enhance their quality, the proposed generator was created using an improved 3D U-Net architecture with skip networks. Nine patients from the 2014 BRATS dataset and nine individuals from the joint hospital dataset were used to train and evaluate the proposed approach at three distinct time occurrences. The average Jaccard index is attained using the suggested GP-GAN [23].

V. Singh et al. developed a CNN model that used deep learning techniques to determine if a tumour was present in an MRI picture. The author trained the model for this binary problem using the VGG-16 model's architecture and weights. This work coupled a CNN model classification issue (determining if a person has a brain tumour or not) with a computer vision problem (automating brain cropping from MRI data). After extracting the features using VGG16, they were fed into an ANN classifier along with additional features using transfer learning. Using a binary classification method, the suggested model, called a Binary Classifier, assesses if a tumour is present in a picture. The system's accuracy increased from 86% on the traditional authentication method to 90% on the CNN model [15].

Using multimodal MRI, A.A. et al. created an ensemble DL-based approach for OS categorization of patients with brain cancer, which enhanced CNN models' performance on constrained volumetric datasets. Originally developed to evaluate 3D MRI data, multi-view CNNs show the data as a sequence of two-dimensional slices in all three orientations (axial, sagittal, and coronal). Next, applying machine learning methods that are often employed in the industry. The probability predicted by the various Multiview CNN models was combined. The suggested method was empirically assessed using a subset of the 163 cases in the BraTS'17 training dataset. The proposed model demonstrated 92.9% accuracy and an AUC in categorizing patients with brain tumor into double OS groups of 0.93 [24].

Computation-based methods for classifying brain tumor were proposed by S. Saeedi et al. In order to detect brain malignancies, researchers created a convolutional auto-encoder system, a unique 2D CNN architecture, and six more popular machine learning methods. For this classification, T1-weighted, contrast-enhanced MRI pictures were utilized; the dataset included a normal brain and three distinct cancer kinds. The findings demonstrated that the proposed neural networks performed better than the baseline methods in identifying brain MRI image characteristics and categorizing them into three cancer classes and one active brain class. It was discovered that the projected auto-encoder system had a training precision of 95.63%, whilst the suggested 2D CNN had a training precision of 96.47%. Six machine learning techniques were developed for the classification of brain tumor in addition to the two deep networks. The KNN (86%) SVM (80%) and RF (82%) produced the best results [25].

Through the use of medical imaging, clinicians have been able to identify cancer thanks to developments in image processing technology over the past 20 years. CAD software has been included into several medical imaging systems and technologies because to its proven ability to increase physicians' positive case identification rate by 10%. Using MRI images, Ghada Saad et al. developed a hybrid algorithm to aid in the detection of brain cancer. By using the suggested method, the author was able to attain a recognition precision of 96.6% [26].

The BCMCNN, CNN hyperparameters are optimized using the ADSCFGWO method, which was suggested by Hanaa ZainEldin et al. A training model constructed using Inception-ResnetV2 is employed following hyperparameter optimization. The model enhances the diagnosis of brain tumors by utilizing popular pre-trained models Inception-ResnetV2. A binary number (0: Normal, 1: Tumour) represents its result. Two main categories may be used to classify hyperparameters: (i) those that specify the fundamental architecture of the network, and (ii) those that regulate network training. The ADSCFGWO algorithm's adaptable architecture combines the advantages of the sine cosine and grey wolf algorithms. The findings of the experiment demonstrate that the BCM-CNN classifier performed better than the others because the CNN optimization hyperparameters improved the CNN's performance. The accuracy of the BCM-CNN on the BRaTS 2021 Task 1 dataset is 99.98% [27].

A CNN was used by A. Chattopadhyay et al. to distinguish brain tumors from 2D MRI data. This method is then used with deep learning as well as traditional classifiers. The researchers gathered a vast amount of MRI images demonstrating various tumour sizes, locations, shapes, and image intensities in order to make sure the system was fully trained. The author also used an SVM classifier and a number of activation strategies (softmax, RMSProp, sigmoid, etc.) to verify the accuracy of the work that was recommended [28].

A CNN was used in a study by M. M. Badza to classify pituitary tumors, meningiomas, and gliomas. The year 2020 saw Badza et al. An input level, two "A" blocks, two "B" blocks, an organization lump, and an output level comprised the investigation's 22-layer network design. The k-fold cross-validation method was used to evaluate the network's efficacy. In this experiment, the tenfold cross-validation method yielded the best results 96.56%. Thirteen and sixty T1-weighted MRI pictures with contrast enhancement were employed in this investigation by K. Suzuki. The Tianjin Medical University, the General Hospital, and the Nanfang Hospital gathered these images in China [5], [29].

Both the dense capsule network (DCNet) and the diversified capsule network (DCNet++) were created by Phaye, Sai Samarth R et al. To learn distinct feature mappings, DCNet only has to incorporate a deeper convolutional network. DCNet++ uses a hierarchical learning architecture to better learn complex data. Only images of three distinct kinds of brain tumor, selected from a set of 3064 MRI scans provided by 233 diagnosed individuals, were used for categorization. Using eightfold cross-validation training, the original eight convolutional layers were reduced to four layers with 16 kernels to create the DCNet model. The success percentage of the DCNet procedure test was 93.04%, while the DCNet++ procedure had a 95.03% success rate [30].

The new automated method created by A. Gumaei et al. can be used by radiologists and doctors to identify brain cancers. The study procedure consisted of three steps: organizing the malignancies from the brain images, preprocessing the images, and feature extraction. Brain pictures were preprocessed to normalize their intensity to a range of [0, 1] via a min-max method. After normalizing the GIST descriptor, author used PCA to extract structures from the MRI pictures. Finally, to identify and classify the various types of cancers, the Regularized Extreme Learning Machine (RELM) organization technique was employed. Researchers employed Cheng's dataset, which contained 3064 MRI images from 233 individuals [31].

Gliomas, meningiomas, and pituitary tumor, all was identified using techniques developed by A. Pashaei et al. Relevant aspects from the photos were chosen using a CNN, and the model's hidden features were retrieved. Four convolutional layers, four pooling levels, four batch regularization levels, and one fully connected level made up the suggested model. Ten epochs with a constant knowledge rate of 0.01 were used in this model. Each epoch had sixteen iterations. This study also made use of the dataset that Cheng supplied. The presentation of the proposed model was evaluated by a tenfold cross-validation exercise, in which 30% of the data was used for system testing and 70% for training. The results demonstrated the excellent accuracy of the proposed approach [32].

This study by A. Rehman et al. looked at three popular CNNs: VGGNet, GoogLeNet, and AlexNet. This work's primary goal was to use deep learning algorithms on processed MRI images to distinguish between brain tumor, including pituitary, glioma, and meningioma glands. Finally, a linear classifier was used to categorize the automated features. By increasing the sample size using data augmentation approaches, overfitting was decreased. Out of all the examined approaches, VGG16 had the greatest accuracy of 98.69%, according to the assessments [33].

By integrating a unique Growing CNN (GCNN) with the Stationary Wavelet Transform (SWT), M. Mittal et al. automated the segmentation process. These methods allowed them to successfully spot cancers in patients' brains using MRI scans. The suggested approach performed better than the genetic algorithm, K-NN, SVM, CNN, and study evaluation findings was better [34].

B. Justin Paulet al. classified pictures of gliomas, meningiomas, and brain malignancies using DL algorithms. The identical dataset (3064 T1-weighted contrast-enhanced MRI brain images from 233 individuals) was used for experimentation. Further, author created two distinct neural network topologies for the task at hand. A five-fold cross-validation process demonstrated that the generic approaches worked better than the specific processes (picture dilation) with a precision of 91.43% [35].

Following table 1, for literature review analysis of recent papers, shows used dataset, methodologies, results and limitations.

Table 1 Literature Review Analysis

Author	Year	Dataset Size	Methodologies	Results	Limitations
A. Chattopadhyay et al.[28]	2022	Brats Dataset, 2020. 2892 pictures in all	CNN	99.74% Accuracy	No Segmentation is carried out.
G. Saad et al.[26]	2023	150 brain MRI pictures	SVM	96.6% Accuracy	Small Size data
S. Saeedi et al.[25]	2023	A collection of 3264 MRI pictures	CNN	96.47%	No ROI or segmentation was carried out.
A.A. MOSSA et. al. [24]	2021	BraTS'17 public datasets (163 images)	CNN	92.9%	No ROI detection is done; only categorization is done.
V. V. S. Sasank et al.[21]	2022	BRATS 2020	CNN	97%	No real time dataset used
H. ZainEldin et al. [27]	2023	BRaTS 2021 Task 1 Dataset	BCM-CNN Inception-ResNet v2	99.98%	Because of the extra optimization steps, processing takes a long time.
Stathopoulos et.al.[36]	2024	A dataset comprising 1646 MRI slices from the examinations of 62 patients	CNN with Transfer Learning	98.6%	Although transfer learning techniques was used, but it may lead to overfitting issues.
Billah, M et.al. [37]	2024	Brain Tumor MRI Dataset	InceptionNet V3 VGG19	Inception Net Validation Accuracy 100% and VGG validation accuracy 95%	Limited Dataset
Li, Zhengkun et.al.[38]	2024	Kaggle-sourced brain tumor MRI dataset consisting 7023 images	six pre-trained models, including ResNet-50, Xception, and InceptionV3	99%	Manual analysis of brain MRI scans is prone to errors, which can be significantly influenced by the radiologists' experience and fatigue.
Oh, Alice et.al. [39]	2024	Medical Images from Kaggle dataset	CNN	91.88%	Missing the novelty and potential impact of the research in advancing the field.
Muftic, Fatima et.al. [40]	2024	MRI Scan Dataset	EfficientNetB3 ResNet50, VGG19	99.44%, 83.62%, 62%	Overfitting, issue with EfficientNetB3 model, also experienced a significant drop in validation accuracy to 89.47%.

III. RESEARCH METHODOLOGY

A research methodology describes the methods and approaches taken to locate and evaluate information pertinent to a certain research question. Scientists employ this strategy to plan their research so they can use the tools of their choosing to accomplish their goals. Every significant facet of research is discussed, including the general framework of the study and methods for gathering, evaluating, and planning data. While these tips may help you comprehend research process, you must recognize the importance of choosing the right strategy.

Our research comes under quantitative research approaches as it uses participant data to anticipate brain tumor and uses the number of participants to ascertain the malignancy or benignity of the brain tumour.

A. Proposed System Architecture

This section will discuss the methods and processes employed in our proposed study, which is illustrated in the accompanying Figure 2, proposed System Architecture.

The proposed system collected data from primary and secondary sources and used image pre-processing algorithms for segmentation, contrast enhancement, and noise reduction. After pre-processing the images for better feature extraction, we will use this picture dataset to train our hybrid neural network model. In order to assess the image collection and validate our proposed method, Brain tumors will subsequently be categorized as either benign or malignant. In the final phase, the number of participants to ascertain the malignancy or benignity of the brain tumor.

1) Data Collection:

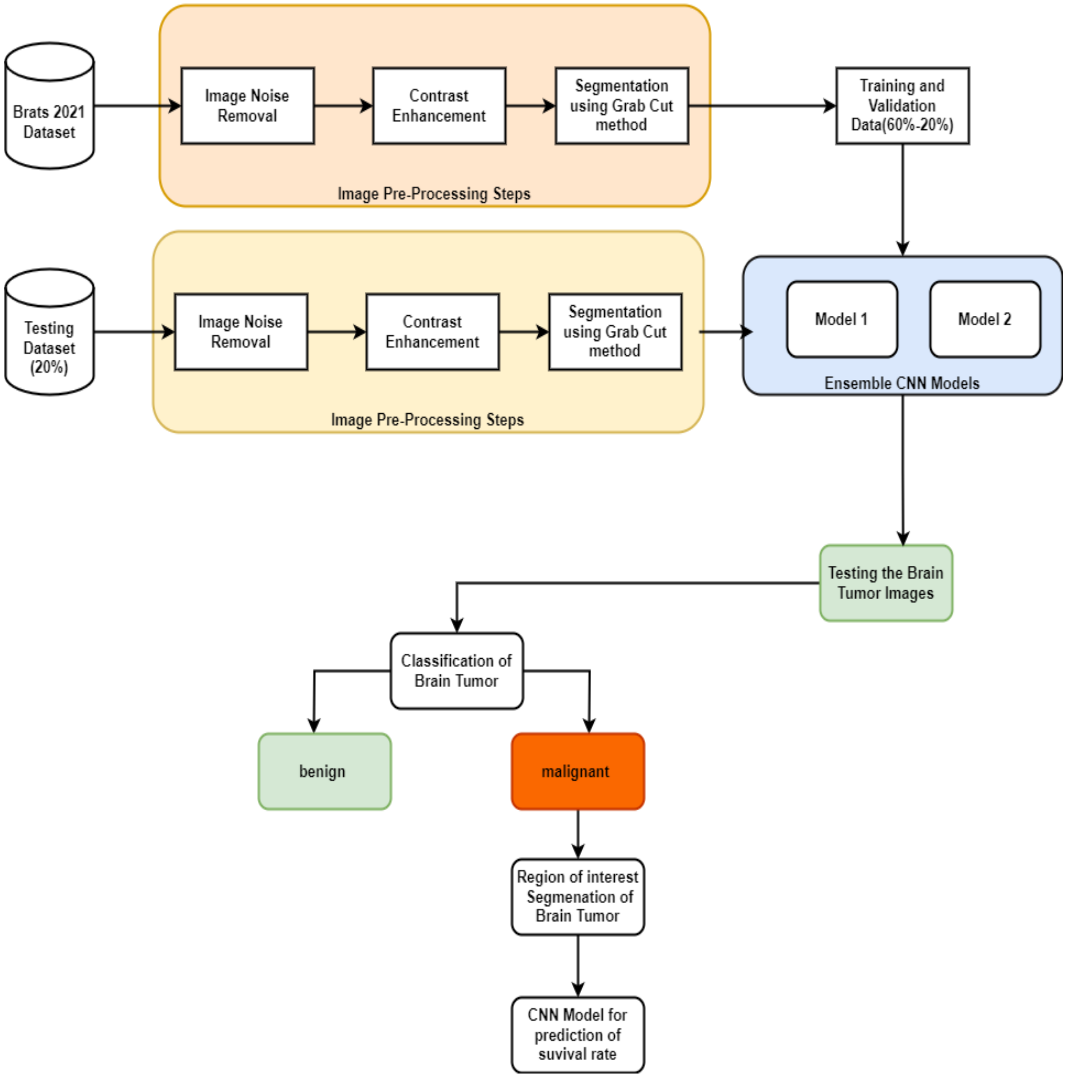

Fig. 2 Proposed System Architecture

Numerous datasets are available of MRI brain images for Brain Tumor classification. After collecting the right piece of data needed for the research, the pre-processing task started where the images made available with labels and encoding. Both primary and secondary sources of information will be used in this section. Twenty percent of the image dataset will be utilized for CNN model testing, while the remaining 80 percent will be used for training and validation.

a) Primary Source of Data: The brain tumour picture dataset from publicly accessible sources, such as the Kaggle platform-based dataset, will be used. The BRaTS 2021 Task 1 Dataset is the name of the dataset. We will thereafter categories this MRI images dataset into brain malignancies as benign or malignant in order to evaluate the picture collection and validate our suggested approach.

b) Secondary Source of Data: We are also employing a secondary source of data to evaluate our study on brain tumour cancer prediction. This source might be the suggested data source, or we could try to get data from a clinical expert. We will use this dataset as a secondary source of information to evaluate our algorithm for brain cancer prediction.

B. Image Pre-processing

Finding the best method for preparing the visual data for neural network training might be difficult. The MRI pictures of brain tumor that have been obtained may have a lot of noise and interruptions throughout the MRI process; therefore, the images must be pre-processed in order to provide excellent results when employing a neural network. This pre-processing step involves scaling the pixel values and employing picture data increase techniques during the model's training and evaluation phases. Determining just how to take images for modelling, such as scaling or normalizing pixel values, can be difficult when using CNN for image categorization. Considerable progress may be made in both the prediction performance of the application of arbitrary adjustments to the image's colour, contrast, brightness, and "photometric distortions." To fit the model's intended input shape, images are resized and various interpolation techniques are selected from a range of options. Some of the following actions will be part of the picture pre-processing steps:

- Noise Reduction: Numerous things, including poor illumination, sensor noise, and errors in compression, can introduce noise into a picture. Removing noise from an image while preserving its essential components is the aim of noise reduction techniques. Some common techniques for noise reduction include Gaussian smoothing, median filtering, and wavelet denoising.
- Contrast Enhancement: Contrast enhancement methods seek to increase contrast in order to facilitate the identification of various components of a picture. Applications for medical imaging and surveillance may benefit from these techniques. Common techniques for improving contrast include histogram equalization, adaptive histogram equalization, and contrast stretching.
- Segmentation: Segmentation methods may be used to separate an image based on the content of each section. When certain organs or structures need to be removed from a picture, segmentation may be useful in applications like medical imaging. Region expansion, edge detection, and thresholding are common segmentation strategies.
- Feature Extraction: Feature extraction techniques are used to find and extract relevant information from an image. These features can be used in applications like photo categorization and object identification. Typical feature extraction techniques include edge detection, corner detection, and texture analysis.

C. Neural Network (NN)

One type of network architecture used to research machine and deep learning is the NN. Deep artificial neural networks, or NNs, are mostly utilized for object recognition in various contexts, picture classification, and image closure based on similarity. NNs are used for object identification, clustering, and image categorization. This definition states that the NN is composed of one or more fully connected layers, one or more convolutional layers, and so forth. It resembles a normal neural network with many layers. The photographs provide it with its information right away. A NN trained to perform image analysis, including classification, object recognition, segmentation, and image processing.

NN is composed of several layers, including the ReLU activation function, Dropout Layer, POOL Layer, Completely Interconnected Layer, NOL, and CL etc.

- Finding local conjunctions of attributes from the preceding layer and transferring them to a map is the main objective of convolution.
- In a CNN, a non-linearity layer comprises an active function that contains an input function map generated by the coevolutionary layer and generates an activation map as an output that will later be used to figure out the network.
- The CNN’s corrective layer is in charge of regulating the components' performance's absolute input volume value.
- Rectified Linear Units (RELUs) are a particular use of CNN that include rectification layers and nonlinearity. One special approach is the combination of rectified and nonlinear layers in ReLUs. One type of layer that gathers data from several sources is called layer pooling. The sample layer for pooling or downgrading reduces the specific size of the activation maps produced by sampling down.
- Fully connected layers: A convolutional network's fully linked layers are multilayer perceptron’s, often consisting of two or three layers. They are made to use the active volumes of the previous layers to map the m1 (l1) m2 (l1) m3 (l1) activation volume in a probability distribution class.
- The Dropout Layer should be used in conjunction with other techniques, such L2 Regularization, to increase the over-fitness of neural networks. One technique for enhancing neural network overfits is the Dropout Layer.
- SoftMax: This function determines the probability distribution of an event in a sequence of occurrences with a maximum of n. In summary, a random number generator is used to determine the chance for each target class over all potential target classes. With the specified inputs, the target class is then selected using the calculated probability. When creating neural networks, softmax functions are utilised at various network layers.

Since we will be working on image-based classification of brain tumor MRI images, we will be focusing on CNN because it is more effective for image classification.

We will use hybrid neural network models of any two of the CNN models available and which will give the best performance results, as determined by the literature review. Depending on the model's performance in picture categorization, early prediction, and correct output, we may also alter the combinations in ensemble models.

IV. Conclusion

To sum up, this study examined many machines learning and deep learning models used for Brain Tumor classification. The literature review examines methods for detecting brain tumor, stressing both their advantages and disadvantages. The literature review also shows how well CNN-based models classified tumor from MRI scans, but it also identified frequent issues such small dataset sizes, a lack of real-time data, and insufficient segmentation methods. In order to get over these restrictions, a hybrid neural network model was proposed by the author, which increases classification accuracy by using sophisticated picture pre-processing and feature extraction. By providing a framework for future advancements in the diagnosis of brain tumor, this study establishes the groundwork for more accurate, dependable, and real-time diagnostic tools. To provide the timely and precise detection of brain tumor, future research should concentrate on improving the scalability of models, integrating more varied information, and honing segmentation approaches.

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