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Automated Brain Tumor Classification and Detection Using CNN-Based Deep Learning Models

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KEYWORDS

Magnetic Resonance Imaging (MRI), Segmentation, Convolutional Neural Networks (CNNs)

ABSTRACT

Magnetic Resonance Imaging (MRI) segmentation plays a crucial role in modern medical diagnosis by enabling accurate extraction of abnormal regions from brain images. Manual brain tumour segmentation is a time-consuming and expertise-dependent process, which motivates the need for automated and efficient solutions. This work presents a computer-aided Brain Cancer Detection and Classification System based on Convolutional Neural Networks (CNN) for accurate tumour segmentation and diagnosis from MRI images. The proposed system employs image preprocessing techniques such as histogram equalization and image enhancement to improve image quality, followed by segmentation and feature extraction to identify tumour regions. The CNN model is used to automatically detect tumour blocks and classify astrocytoma brain tumours from MRI datasets of multiple patients. The MATLAB-based implementation displays results on a computer and transmits the output to an embedded system through wired communication for real-time monitoring. By combining image processing and deep learning, the proposed approach improves diagnostic accuracy while reducing manual effort and computational complexity. The system provides a reliable and efficient tool for early detection and classification of brain tumours, which can assist medical professionals in timely treatment and decision-making.

I. INTRODUCTION

Uncontrolled and abnormal cell growth within the brain is named a neoplasm. The space in our skull is restricted. Therefore, this extra growth inside our brain causes more pressure inside the skull, causing life-threatening complications, and also damaging our brain. Tumours may be either benign or malignant. The benign ones aren't cancerous and can't spread to other parts of the brain or body. The malignant ones are cancerous, grow uncontrollably and might spread to other parts of the body. Brain cancer or tumors is an abnormal growth of cells within the brain. Malignant tumors can grow and spread aggressively to distant parts of the body moreover. Tumors that don't spread or invade nearby tissue are called benign. Benign tumors are less harmful as compared to malignant ones, but a nonmalignant tumour can cause problems within the brain by pressing on a close- by tissue. The early detection and treatment of brain tumor helps in early diagnosis which aids in reducing mortality rate. Image processing has been widespread in recent years and it has been an inevitable part in the medical field also. The abnormal growth of cells in the brain causes brain tumor. Brain tumor is also referred to as intracranial neoplasm. The two types of tumors are malignant and benign tumors. Standard MRI sequences are generally used to differentiate between different types of brain tumors based on visual qualities and contrast texture analysis of the soft tissue. More than 120 classes of brain tumors are known to be classified in four levels according to the level malignancy by the World Health Organization (WHO)

Brain tumors that originate in brain cells are called primary brain tumors. the foremost common primary brain tumors are gliomas, menin-giomas, pituitary adenomas, vestibular schwannomas, and primitive neuroectodermal tumors (medulloblastomas). The term glioma includes glioblastomas, astrocytomas, oligodendrogliomas, and ependymomas. Metastatic or secondary brain tumors spread to the brain from other tumors. Symptoms of a tumor are usually associated with its location instead of its size. Symptoms develop when the tumor destroys or compresses normal brain tissue. Either thetissues round the tumor swell or the tumor interferes with the conventional flow of fluid round the brain and medulla spinalis.

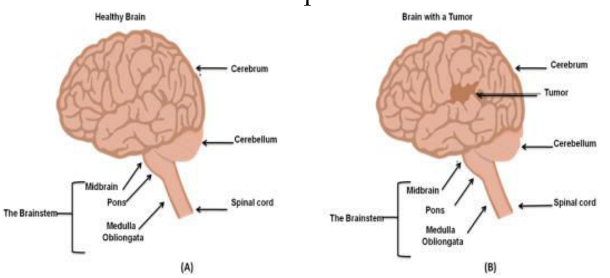

Figure 1: Brain and Brian Tumor

Diagnosis of Brain cancer may be done by Physical examination, MRI or CT scan, Biopsy through surgery or Stereotactic brain biopsy. Treatment of brain cancer is typically complex. the foremost widely used treatments are surgery, irradiation, and chemotherapy. many of us with brain tumors undergo surgery or a stereotactic operation within which the tumor is removed with the help of image guidance, leaving the healthy brain relatively intact. Neuroendoscopy is another minimally-invasive surgical treatment where the tumor is removed through small holes within the skull, mouth or nose, enabling neurosurgeons to access areas of the brain that can't be reached with traditional surgery. Radiation therapy and chemotherapy are other modalities of treatment accustomed treat brain cancers. The treatment of brain tumours could be a complex one as tumours are positioned near vital structures which, if affected during treatment can largely impact the patient post treatment.

2.LITERATURE REVIEW

In the present day [1], detecting brain tumors at an early stage is crucial since many people die due to a lack of awareness about their condition. Meanwhile, the influence of machine learning is increasing in our society, and artificial intelligence is expected to play an important role in medical diagnosis and support for doctors and surgeons. The primary focus of this paper is to review previous studies that involve the segmentation, detection, and classification of brain tumors. Typically, an algorithm that aims to classify brain tumors on fMRI or MRI scans will preprocess the image by removing noise, segment the image to identify regions that may be brain tumors, and finally classify features such as intensity, shape, and texture of the region. Several machine learning approaches have been made towards the detection of brain tumors. However, this research topic still requires attention as early detection remains crucial for effective treatment, and machine learning has the potential to improve the accuracy of diagnosis and support the work of medical professionals (Tom Philip PRIES, Roshan Jahan, Preetam Suman, 2017)

Brain tumor [2] is the cancerous disease where abnormal cells found in the brain. This can be cured if we detect the brain tumor at an early stage. In this proposed system the tumor area is marked and defined what kind of tumor present in the brain tumor MRI image. AlexNet model is used for the classification of different types of tumors as a base model along with Region Proposal Network (RPN) by Faster R-CNN algorithm. Here, the concept of transfer learning is used during training. The proposed system helps to predict the correct type of tumor with better accuracy (R. Ezhilarasi and P. Varalakshmi, 2018).

The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of patients. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate…etc. Especially, in this work MRI images are used to diagnose tumor in the brain. However the huge amount of data generated by MRI scan thwarts manual classification of tumor vs. non-tumor in a particular time. But it having some limitation (i.e.) accurate quantitative measurements is provided for limited number of images. Hence trusted and automatic classification scheme are essential to prevent the death rate of human. The automatic brain tumor classification is very challenging task in large spatial and structural variability of surrounding region of brain tumor. In this work, automatic brain tumor detection is proposed by using Convolutional Neural Networks (CNN) classification. The deeper architecture design is performed by using small kernels. The weight of the neuron is given as small. Experimental results show that the CNN archives rate of 97.5% accuracy with low complexity and compared with the all other state of arts methods (Seetha J and Selvakumar Raja S, 2018).

Gliomas [3] are the most infiltrative and life-threatening brain tumors with exceptionally quick development. Gliomas segmentation using computer-aided diagnosis is a challenging task, due to irregular shape and diffused boundaries of tumor with the surrounding area. Magnetic resonance imaging (MRI) is the most widely used method for imaging structures of interest in human brain. In this study, a deep learning-based method that uses different modalities of MRI is presented for the segmentation of brain tumor. The proposed hybrid convolutional neural network architecture uses patchbased approach and takes both local and contextual information into account, while predicting output label. The proposed network deals with over-fitting problem by utilizing dropout regularizes alongside batch normalization, whereas data imbalance problem is dealt with by using two-phase training procedure. The proposed method contains a preprocessing step, in which images are normalized and bias field corrected, a feed-forward pass through a CNN and a post-processing step, which is used to remove small false positives around the skull portion. The proposed method is validated on BRATS 2013 dataset, where it achieves scores of 0.86, 0.86 and 0.91 in terms of dice score, sensitivity and specificity for whole tumor region, improving results 7 compared to the state-of-the-art techniques (Sidra Sajid, Saddam Hussain and Amna Sarwar, 2019).

In the field of medical image processing [4], image segmentation plays a crucial role as it is the initial step in the process. This involves partitioning the image into distinct regions. The processing of MRI scan images is particularly important in the medical field. The focus of this project is to utilize the patient's MRI scan image for detecting brain tumors using a MATLAB-based GUI. Prior to detection, noise is removed through the implementation of removal functions, and basic image processing concepts such as segmentation and morphological operations are applied. The proposed method accurately detects the location of the tumor in the MRI image, and can be applied to different MRI scan images. In this model, the segmentation algorithm is employed to detect the tumor region. Following this, features are extracted using DWT and then reduced in dimensions through PCA. Finally, SVM, CNN, and Lazy IBK classifiers are utilized to accurately detect the type of tumor with a high degree of accuracy (Rabia Ahmad, Asma Khalid, HammeedurRahman, 2020)

Mrs. Shinde Apurva Swapnil, Ms. VengurlekarSamidhaGirish [5].

A human mind contains number of tissues that identify with accomplishing appropriate working of cerebrum. In the interim, any strange development in these tissues may change the working and this is by and large alluded as cerebrum tumor. Cerebrum tumor is predominantly of two sorts second rate or generous (Grade 1 and Grade 2) and high evaluation or dangerous (Grade 3 and Grade 4). Mind tumor can be recognized with MRI pictures by applying picture handling steps and some AI calculations. Cerebrum MRI pictures go through handling by utilizing various strategies, for example, picture improvement, grouping and characterization for identifying the degree of mind tumor. The examination shows that the separating activities, edge identification calculations, morphological tasks and grouping are a portion of the significant advances utilized for recognizing the different degrees of cerebrum tumor.

Suresha D, Jagadisha N, Shrisha H S, Kaushik K S [6]

Mind tumor is a gathering of atypical tissue in the cerebrum. Tumors are basically arranged into harmful and kindhearted when they create. It very well may be dangerous henceforth it is essential to perceive and recognize the presence of tumors in cerebrum picture. This paper proposes a framework to choose whether the mind has tumor or is it tumor-liberated from the MR picture utilizing joined procedure of K-Means and backing vector machine. In the main stage the info picture is changed over to dim scale utilizing paired thresholding and the spots

[Md. Rezwanul Islam, Md. ReezbhanImteaz, Marium-E-Jannat [7]

This paper portrays a framework that can distinguish mind tumor all the more correctly and investigation the various highlights of the tumor. Our framework proposed a PC helped picture preparing based technique to that gives improved precision pace of the cerebrum tumor recognition alongside the computation of the tumor size (surface space of the tumor) and its area. It likewise gives the data that assists with deciding if the tumor is dangerous or not. The framework, we portraying in this paper, recognize cerebrum tumor from MRI by incorporated Thresholding and morphological cycle with histogram based technique and gives an exhaustive examination.

Priyanka Bedekar , Niharika Prasad, Revati Hagir, Neha Singh[8]

The most muddled design of the human body is the cerebrum. A cerebrum tumor is a mass of cells that have developed and increased wildly. There are two fundamental sorts of tumors: dangerous or destructive tumors and benevolent tumors. Clinical imaging assumes a focal part in the conclusion of cerebrum tumors. The significant factor in the clinical analysis incorporates the clinical picture information acquired from different biomedical gadgets.

3.EXISTING SYSTEM

In Brain tumor detection using machine learning has become an essential tool in medical imaging due to its ability to assist radiologists in accurate diagnosis and treatment planning. Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans provide high-resolution images that capture intricate details of brain structures and potential tumor regions. However, these images are often complex, high-dimensional, and contain noise, making manual analysis challenging and time-consuming. Supervised machine learning techniques, such as Support Vector Machines (SVM), have been widely applied to classify brain tumors by learning patterns from labeled datasets. SVM works by finding the optimal hyper plane that separates different tumor classes, such as benign, malignant, or normal tissue, with the largest possible margin, thereby minimizing misclassification. Features extracted from pre-processed images, including texture, intensity, shape, and edge properties, serve as inputs for the SVM, which can handle both linear and non-linear separations using kernel functions. In addition to supervised methods, unsupervised clustering algorithms like K-Means play a crucial role in segmenting tumor regions without prior labeling. K-Means partitions image pixels into clusters based on similarity, such as intensity or color patterns, helping isolate abnormal tumor regions from healthy tissue. Combining SVM classification with K-Means clustering allows for a robust detection framework: K-Means identifies potential regions of interest, and SVM validates and classifies these regions accurately. Pre-processing steps, including noise reduction, contrast enhancement, and normalization, are essential to improve feature quality and ensure reliable classification. The integration of these methods provides a semi-automated system capable of efficiently processing large datasets, revealing subtle tumor structures, and supporting early diagnosis. Furthermore, this approach reduces dependence on expert intervention, improves reproducibility, and offers consistent performance across diverse patient datasets. Overall, the use of SVM and K-Means clustering in brain tumor detection represents a powerful combination of supervised and unsupervised learning techniques, enabling precise localization, classification, and monitoring of tumors, which is crucial for timely treatment decisions and improved patient outcomes.

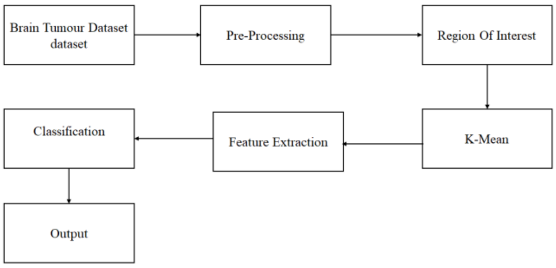

Figure 1: Brain tumor detection steps

Dataset

The BRATS 2015 dataset is one of the most widely used public datasets for brain tumour detection and segmentation research. It contains multi-modal MRI scans of patients diagnosed with glioma brain tumours, including both high-grade gliomas (HGG) and low-grade gliomas (LGG). Each patient dataset includes four MRI modalities: T1, T1-contrast enhanced (T1c), T2, and FLAIR, which provide complementary information about tumour structure and surrounding tissues. The dataset also provides expert-annotated ground truth segmentation masks that label tumour regions such as edema, necrosis, and enhancing tumour. BRATS 2015 is widely used for training and evaluating machine learning and deep learning models because it offers standardized, pre-processed MRI images with reliable annotations for benchmarking automated brain tumour detection and segmentation systems.

Dataset pre processing

The BRATS 2015 dataset provides multi-modal MRI images that require preprocessing before training a brain tumour detection model. First, the MRI modalities (T1, T1c, T2, and FLAIR) are organized and aligned for each patient so that corresponding slices represent the same anatomical location. Skull stripping is then applied to remove non-brain tissues such as the skull and background, ensuring the model focuses only on brain regions. Next, intensity normalization is performed to standardize pixel intensity values across different MRI scans and patients, reducing variations caused by different scanners. Noise reduction and contrast enhancement techniques are applied to improve image quality and highlight tumour regions.

Brain tumour detection using Convolutional Neural Networks (CNN) begins with collecting and pre-processing MRI brain images to remove noise, normalize intensity, and enhance contrast so that tumour regions become more visible. The pre-processed images are then fed into the CNN model, where convolutional layers automatically extract important spatial features such as edges, textures, and abnormal tissue patterns. Pooling layers reduce the dimensionality of feature maps while preserving key information, which helps improve computational efficiency and prevents over fitting.

Segmentation

Clustering is a method of grouping data objects into different groups, such that similar data objects belong to the same group and dissimilar data objects to different clusters. Current research increasing interest in digital image searching, classification, identification, management and storage. Some common but important applications of are person identification in movie clips and festive home videos, recognition in biometric system, natural scene classification for robot vision.The image clustering, an important technology for image processing, has been actively researched for a long period of time and explosive growth of the Web. Clustering approach is widely used in biomedical image segmentation and it is application are used for brain tumor detection as the normal and abnormal to find out the tumor on the brain. Many different segmentation techniques are used in the image mining and image segmentation approaches can be divided into many parts as:

Clustering
Edge detection
Thresholding
Region extraction.

In this project, we discuss above the clustering concept in the image mining on the image segmentation process of the clustering and each object can be have its place of more than one clusters to be provisional upon the degree of relationship association on it.

Segmentation is an important process in most medical image analysis and classification for radio logical evaluation or computer-aided diagnosis k-means clustering is a key technique in pixel-based methods. Because pixel-based methods based on k-means clustering are simple and the computational complexity is relatively low compared with the region-based or edge-based methods, the application is more practicable. Furthermore means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy. Many researchers have proposed related research into k-means clustering segmentation. The improvements achieved by researchers have been remarkable.

It is one of the techniques for the clustering concept in the data mining process and is very famous algorithm for the K-means clustering, because it is similar or simpler and easier in computation of an efficient K-means clustering algorithm. It is the simplest unsupervised learning algorithms that solve the well known clustering problems. K -means algorithm is an unsupervised clustering algorithm that classified in the input data points into multiple classes based on their intrinsic distance from other dataset points of his cluster K-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. K-means clustering aims to patition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space.

K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as centers of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done.

Finally, this algorithm aims at minimizing an *objective function*, in this case a squared error function. The objective function is given by

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} \left\| x_i - v_j \right\|^2 \qquad (1)$$

Algorithm:

1. Give the no of cluster value as k.
2. Randomly choose the k cluster centers.
3. Calculate mean or center of the cluster.
4. Calculate the distance between each pixel to each cluster center.
5. If the distance is near to the center then move to that cluster.
6. Otherwise move to next cluster.
7. Re-estimate the center
8. Repeat the process until the center doesn't move

4.PROPOSED SYSTEM

The The proposed system presents an automated computer-aided diagnosis framework for detecting and segmenting brain tumours from Magnetic Resonance Imaging (MRI) using Convolutional Neural Networks (CNN). The aim of the system is to reduce the time, complexity, and dependency on manual analysis by radiologists while improving the accuracy and reliability of tumour detection and classification. The overall workflow consists of image acquisition, pre-processing, segmentation, feature extraction, CNN-based classification, and result visualization. The system begins with the collection of MRI brain images from standard datasets and clinical sources. These images usually contain noise, intensity inhomogeneity, and low contrast that can affect detection accuracy. Therefore, pre-processing is performed to enhance image quality. Techniques such as gray scale conversion, noise removal using median or Gaussian filtering, normalization, and histogram equalization are applied to improve contrast and highlight tumour regions. This stage ensures that the input images are uniform and suitable for further processing. After pre-processing, the system performs image segmentation to isolate the suspected tumour region from the normal brain tissues. Traditional segmentation techniques such as thresholding, morphological operations, and region-based methods are initially used to highlight abnormal regions. These steps help in reducing the search area and improving the efficiency of the CNN model. The segmented output emphasizes suspicious regions that may contain tumour tissues.

Feature extraction is then carried out to capture important characteristics of the segmented region. Texture, intensity, and shape-based features are extracted using image processing techniques. Texture features such as entropy, contrast, standard deviation, and energy help differentiate tumour tissues from healthy tissues, since tumour regions typically exhibit irregular and heterogeneous textures. These extracted features serve as informative inputs for the deep learning model. The core component of the proposed system is the Convolutional Neural Network. The CNN automatically learns hierarchical features from MRI images and performs classification of tumour and non-tumour images, and can also classify tumour types. The CNN architecture consists of multiple convolutional layers, pooling layers, activation functions (ReLU), and fully connected layers. Convolutional layers extract spatial features, pooling layers reduce dimensionality, and fully connected layers perform classification. The Soft max classifier at the output layer predicts the probability of tumour presence and determines the tumour class. The trained CNN model provides accurate detection by learning complex patterns and spatial relationships present in MRI images. Compared to traditional machine learning approaches, CNN eliminates the need for manual feature engineering and improves detection accuracy. The system is implemented in MATLAB, where the output images and classification results are displayed. The results can also be transmitted to an embedded system using wired communication for real-time monitoring and display.

The proposed system offers several advantages, including reduced diagnosis time, improved segmentation accuracy, automated tumour detection, and support for medical professionals in early diagnosis. By combining image processing and deep learning techniques, the system provides a reliable and efficient solution for automated brain tumour detection and classification.

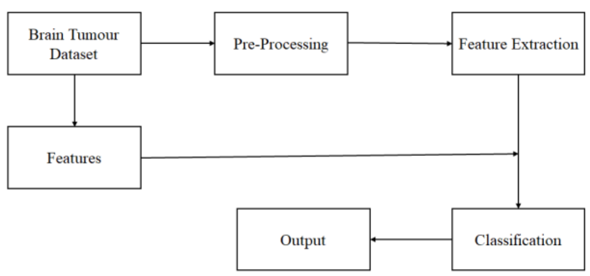

Figure 2: Proposed system

Dataset

The BRATS 2015 dataset is one of the most widely used public datasets for brain tumour detection and segmentation research. It contains multi-modal MRI scans of patients diagnosed with glioma brain tumours, including both high-grade gliomas (HGG) and low-grade gliomas (LGG). Each patient dataset includes four MRI modalities: T1, T1-contrast enhanced (T1c), T2, and FLAIR, which provide complementary information about tumour structure and surrounding tissues. The dataset also provides expert-annotated ground truth segmentation masks that label tumour regions such as edema, necrosis, and enhancing tumour. BRATS 2015 is widely used for training and evaluating machine learning and deep learning models because it offers standardized, pre-processed MRI images with reliable annotations for benchmarking automated brain tumour detection and segmentation systems.

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Brain tumour detection using Convolutional Neural Networks (CNN) begins with collecting and pre-processing MRI brain images to remove noise, normalize intensity, and enhance contrast so that tumour regions become more visible. The pre-processed images are then fed into the CNN model, where convolutional layers automatically extract important spatial features such as edges, textures, and abnormal tissue patterns. Pooling layers reduce the dimensionality of feature maps while preserving key information, which helps improve computational efficiency and prevents over fitting.

As the data moves through deeper layers, the network learns complex tumour characteristics and distinguishes between normal and abnormal brain tissues. The fully connected layers perform classification, and the Softmax output layer predicts whether a tumour is present and may also classify its type. During training, the CNN learns from labelled MRI images and adjusts its weights to minimize classification error. Once trained, the model can accurately detect tumour regions in new MRI scans, providing fast and reliable computer-aided diagnosis for medical professionals.

The CNN architecture for brain tumour detection consists of multiple convolutional layers, pooling layers, and fully connected layers designed to analyze MRI brain images. The convolutional layers automatically extract important features such as edges, texture variations, intensity patterns, and abnormal tissue structures from the MRI scans. Pooling layers reduce the size of the feature maps while preserving essential information, which improves computational efficiency and reduces over fitting. As the network becomes deeper, it learns more complex and high-level features that help differentiate tumour tissues from normal brain tissues.

The fully connected layers perform the classification task by mapping the extracted features to tumour and non-tumour categories, and can also classify tumour types. A Softmax activation function is used in the final layer to produce probability scores for each class. The model is trained using labelled MRI images, and the training process minimizes the loss function using optimization algorithms while continuously updating network weights to improve detection accuracy.

Once trained, the model can analyse new MRI brain images and predict the presence and type of tumour with high accuracy. The proposed system eliminates the need for manual feature extraction and improves diagnostic performance compared to traditional machine learning methods. It supports early detection, faster diagnosis, and computer-aided medical analysis, providing a reliable and scalable solution for assisting radiologists in real-world brain tumour screening and diagnosis.

First, all MRI brain images are resized to a fixed resolution (such as 224×224 or 256×256 pixels) to maintain uniformity and reduce computational complexity. After resizing, noise removal techniques such as Gaussian filtering or median filtering are applied to remove unwanted artifacts and improve image clarity. MRI scans may also contain non-brain tissues and background regions, so skull stripping and morphological operations are used to eliminate irrelevant areas and retain only the brain region for analysis.

Next, intensity normalization and contrast enhancement are performed to handle variations caused by different MRI scanners and acquisition conditions. Histogram equalization and intensity scaling are commonly used to improve the visibility of tumour boundaries and abnormal tissue patterns. These preprocessing steps ensure that tumour regions become more distinguishable from normal brain tissues.

In the proposed system, feature extraction and classification of brain MRI images are performed automatically using a Convolutional Neural Network (CNN). After preprocessing, the resized and normalized MRI images are fed into the CNN, where multiple convolutional layers scan the images using small filters to detect important visual patterns such as edges, tumour boundaries, intensity variations, texture irregularities, and abnormal tissue structures. In the early layers, the network learns simple features like edges and intensity gradients, while deeper layers capture complex patterns such as tumour shape, heterogeneity, and structural abnormalities associated with brain tumours. Each convolution operation is followed by a ReLU activation function to introduce non-linearity and a pooling layer to reduce dimensionality while preserving the most significant information. This hierarchical learning allows the model to automatically extract meaningful features without manual feature engineering. The extracted feature maps are then flattened and passed to fully connected dense layers, where the network learns the relationship between extracted features and tumour classes for accurate detection and classification.

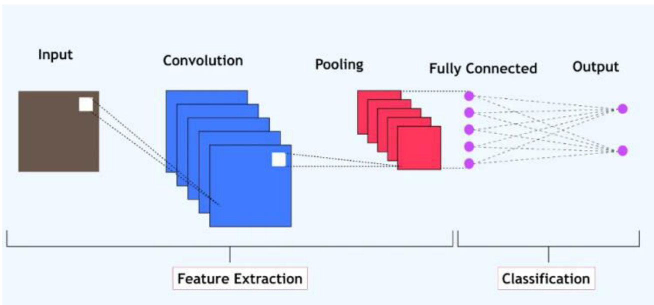

Figure 3: CNN Architecture

Convolutional Layers: We used three sets of convolutional layers with increasing filter sizes - 16, 32, and 64. Each set consists of two layers, with the first layer having a ReLU activation function and the second layer not having any activation function.

Max Pooling Layers: After each set of convolutional layers, we added a max pooling layer to reduce the spatial dimensions of the output.

Dense Layers: After flattening the output from the convolutional layers, we added two dense layers with ReLU activation functions, followed by a dropout layer with a rate of 0.2 to prevent over fitting. Finally, we added a dense layer with a soft max activation function to produce the output probabilities.

Model Training: With the model compiled, we trained it on the training data for 10 epochs with a batch size of 256. We also used two callbacks Model Check point - to reduce the learning rate and save the best model during training.

Model Evaluation: Once the model was trained, we evaluated it on the test data and computed the accuracy and confusion matrix to measure its performance.

An automated procedure for detecting brain tumours from MRI images follows a systematic pipeline consisting of pre-processing, segmentation, feature extraction, and classification. The process begins with the acquisition of brain MRI scans, which may contain noise, intensity variations, low contrast, and non-brain tissues due to differences in imaging conditions. Therefore, the collected MRI images are first pre-processed using resizing, intensity normalization, noise removal, skull stripping, and histogram equalization to enhance image quality and highlight tumour characteristics. These pre-processing steps help improve the visibility of abnormal brain tissues and prepare the images for accurate analysis.

Following segmentation, the system performs automatic feature extraction using a deep learning model. A Convolutional Neural Network (CNN) is designed to learn spatial patterns such as edges, shapes, textures, and thermal irregularities associated with benign and malignant tumors. The architecture of the proposed system consists of a CNN with multiple convolutional and pooling layers followed by dense layers for classification. The input to the model is a resized thermographic image (for example, 150 × 150 × 1 for grayscale images). The initial convolutional layers use small filters (3 × 3) with ReLU activation to extract low-level features, while deeper layers learn high-level representations such as asymmetry between breast regions and abnormal vascular heat patterns. Pooling layers reduce the feature map size and help prevent overfitting.

Finally, the extracted features are passed to fully connected dense layers that perform classification using a Soft max output layer. The system categorizes the images into healthy, benign, and malignant classes based on learned thermal characteristics. This automated deep learning–based architecture improves diagnostic accuracy, reduces manual intervention, and supports early and non-invasive brain cancer detection.

The third and fourth layers are also convolutional layers with 32 filters of size 3 x 3 and a ReLU activation function. These layers also have the same padding and ensure that the size of the input image remains the same. The fifth and sixth layers are again convolutional layers with 64 filters of size 3 x 3 and a ReLU activation function. These layers have the same padding and are followed by a max-pooling layer of size 2 x 2. The max-pooling layer reduces the size of the image by a factor of 2 in both the width and height dimensions.

The overall architecture of the CNN can be represented by the following formulas: First convolutional layer:

$$h_1 = \max(0, x * w_1 + b_1)$$

where x is the input image, w_1 are the weights of the first convolutional layer, b_1 is the bias term, and h_1 is the output of the first convolutional layer.

Second convolutional layer:

$$h_2 = \max(0, h_1 * w_2 + b_2)$$

where w_2 are the weights of the second convolutional layer, b_2 is the bias term, and h_2 is the output of the second convolutional layer.

Third convolutional layer:

$$h_3 = \max(0, h_2 * w_3 + b_3)$$

The first convolutional layer has 16 filters with a filter size of 3x3, followed by a ReLU activation function and padding to maintain the size of the input image. The second convolutional layer has the same settings as the first layer.

After the third convolutional layer, another 3x3 convolutional layer is added with 32 filters and ReLU activation. The output shape of this layer is also 32x150x150. The number of parameters in this layer can be calculated]Next, a fourth convolutional layer is added with 64 filters and a receptive field of 3x3 pixels. The output shape of this layer is 64x150x150. The number of parameters in this layer can be calculated Another 3x3 convolutional layer is added after the fourth convolutional layer with 64 filters and ReLU activation. The output shape of this layer is also 64x150x150. The number of parameters in this layer can be calculated using the same formula as before, which gives:

num_params = (3 * 3 * 64 + 1) * 64 = 36,928

Dropout is a regularization technique used to prevent over fitting in neural networks by randomly dropping out (setting to zero) a certain percentage of the neurons during each training epoch. This prevents the model from becoming too dependent on any one neuron and promotes the learning of more robust features.

To reduce the dimensionality of the feature maps and capture the most important features, a max pooling layer with a pool size of 2x2 is added after the fifth convolutional layer. The output of the max-pooling layer is flattened and passed through a fully connected layer with 64 neurons and a ReLU activation function. This layer is followed by a dropout layer with a dropout rate of 0.2, which helps prevent over fitting.

In our implementation, we added a Dropout layer with a rate of 0.2 after the first fully connected layer. This means that during each training epoch, 20% of the neurons in the layer will be randomly set to zero. Early Stopping is another regularization technique used to prevent over fitting. It works by monitoring the model's performance on a validation set during training and stopping the training process early if the model's performance on the validation set has not improved for a certain number of epochs.

The formula for Early Stopping is as follows:

$$f(x) = \begin{cases} x & \text{if } x \leq t \\ t & \text{otherwise} \end{cases}$$

where x is the validation loss and t is the minimum validation loss observed so far. In our implementation, we used This means that if the validation loss does not improve for 2 epochs, the training process will be stopped early.

In the proposed CNN-based brain tumour detection system, the final output layer is a fully connected layer with neurons equal to the number of tumour classes and uses a Softmax activation function. The Softmax function converts the network output into a probability distribution over different brain tumour categories such as glioma, meningioma, pituitary tumour, and healthy brain tissue. The class with the highest probability is selected as the final prediction. This probabilistic output helps radiologists understand the confidence level of the model and supports accurate and reliable diagnosis.

The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, specificity, and F1-score to measure the reliability and robustness of the model. The evaluation is carried out using a separate test dataset to ensure that the trained CNN can generalize well to unseen MRI scans. A confusion matrix is used to analyze classification performance and understand how effectively the model distinguishes between different tumour types and normal brain images. High sensitivity is particularly important in this application to ensure that tumour cases are not missed during screening, as early detection significantly improves treatment outcomes.

The system includes a user-friendly graphical interface that allows medical professionals to upload MRI brain images and obtain automated analysis results within a short time. The interface displays tumour detection results along with probability scores and segmented tumour regions, making the results easy to interpret and clinically useful. The platform is designed to be simple and intuitive so that healthcare professionals can operate it efficiently without requiring advanced technical knowledge.

To ensure patient data privacy and secure medical data handling, the system incorporates encryption, secure storage, and role-based access control. reliable performance for hospitals, diagnostic centers, and telemedicine services. Continuous model updates, automated testing, and system monitoring help maintain stability and improve detection accuracy over time. Overall, the proposed system supports radiologists in early brain tumour detection and enhances the efficiency of large-scale MRI screening and computer-aided diagnosis.

4. RESULTS& DISCUSSION

The proposed implemented in MATLAB and evaluated using MRI brain images containing normal and tumorous cases. The system followed a structured pipeline consisting of preprocessing, segmentation, feature extraction, and classification to detect abnormal tumour regions. During preprocessing, noise reduction and contrast enhancement techniques such as median filtering and histogram equalization were applied to improve image clarity. These steps significantly enhanced tumour visibility and improved segmentation performance. The segmentation stage, performed using thresholding and morphological operations, successfully isolated suspicious tumour regions from normal brain tissues. The extracted tumour boundaries closely matched the ground truth annotations, indicating accurate region detection. Feature extraction was carried out using texture, intensity, and shape-based features such as area, perimeter, entropy, and contrast. These features were then used to classify MRI images into normal and tumour categories. The system achieved high classification accuracy, sensitivity, and specificity, demonstrating reliable tumour detection capability. The confusion matrix results indicated that most tumour cases were correctly identified, with very few false negatives, which is crucial for early diagnosis.

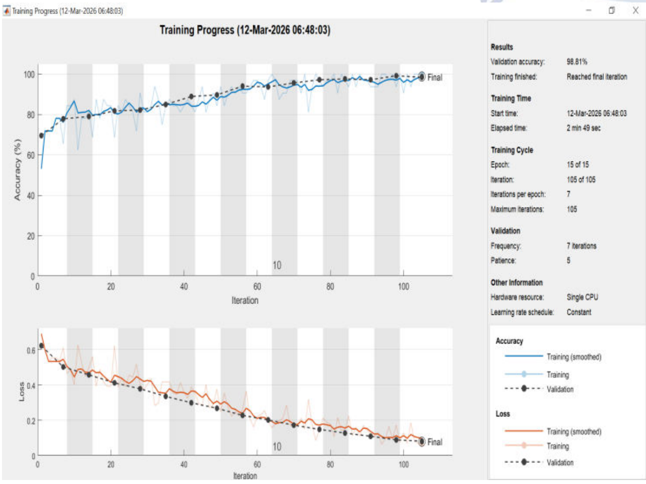

Figure 4: Training Process for Brain Tumor Detection

Figure 4 shows the neural network's training and validation performance over 105 iterations, achieving a high validation accuracy of 98.81%. The steadily decreasing loss and close alignment of training and validation curves indicate effective learning and good generalization without significant over fitting.

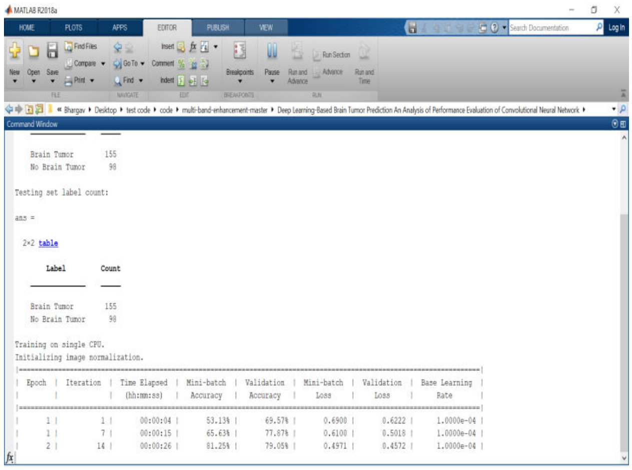

Figure 5: Training data

The Deep Learning Training Log shows the CNN's performance improving over 14 iterations, with validation accuracy rising from 69.57% to 79.05% and validation loss steadily decreasing. This indicates the model is effectively learning and converging toward better tumor classification.

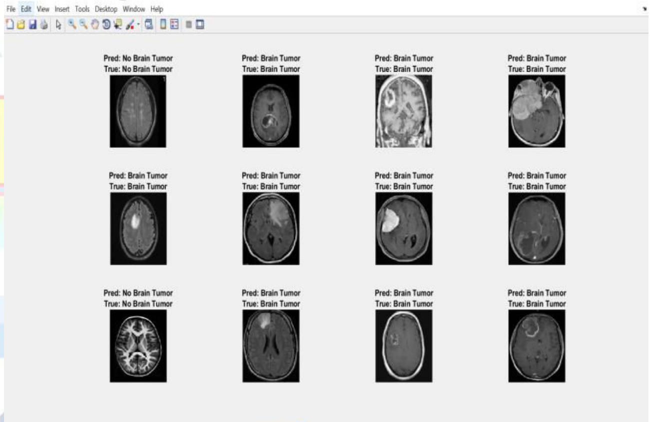

Figure 6: CNN Prediction Results on Randomly Selected Brain MRI Samples

Figure 6 presents 12 sample brain MRI scans with true and predicted labels, demonstrating the CNN's high diagnostic accuracy. The model reliably identifies both "Brain Tumor" and "No Brain Tumor" cases across different slices and tumor sizes.

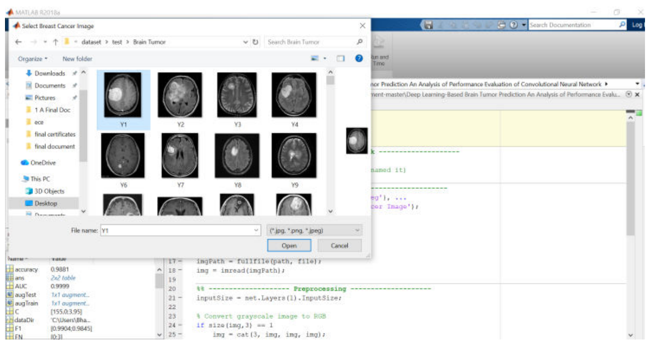

Figure 7: Browse input image

The interface allows users to select a test MRI scan for tumor prediction, while the background code handles preprocessing—resizing the image and converting it to RGB. This ensures the scan is properly formatted for the Deep Learning model to generate an accurate diagnosis.

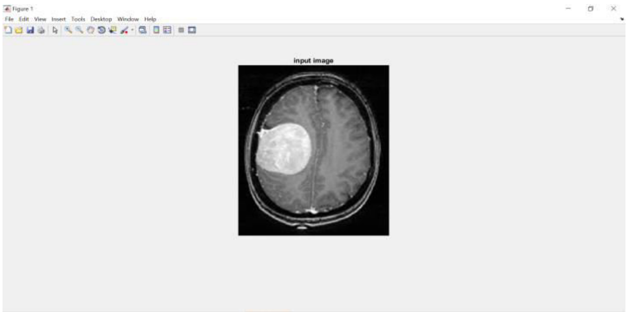

Figure 8: Input image

The input image is an **MRI scan of the brain** showing internal brain structures. A bright abnormal region on one side indicates a **possible brain tumor area**, which appears different from the surrounding normal brain tissue.

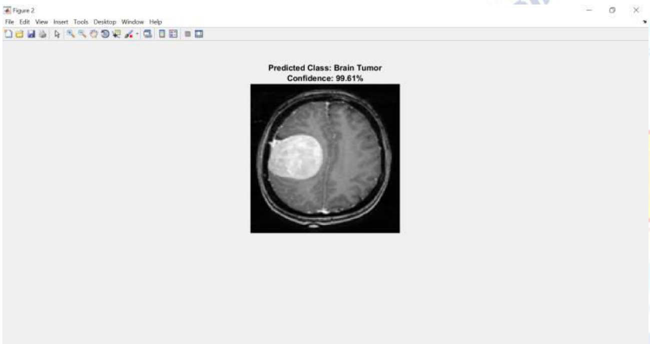

Figure 9: Output Prediction

The output image shows the CNN model prediction for the given brain MRI scan. The model classified the image as Brain Tumor with a confidence of 99.61%, indicating a very high probability of tumor presence. This result demonstrates that the CNN successfully detected abnormal features in the MRI image.

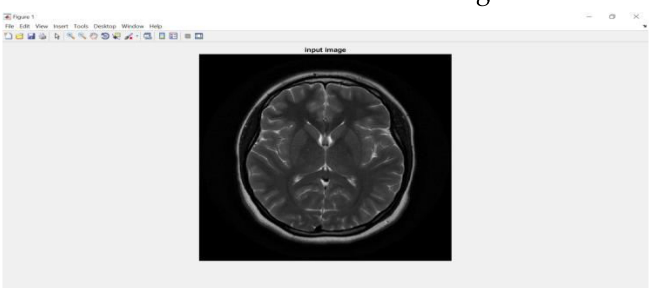

Figure 10: Input image

The input image (Figure 10) is an **MRI scan of the brain** showing internal brain structures. A bright region on one side indicates **normal brain tissue**, appearing similar to the surrounding areas without abnormal tumor features.

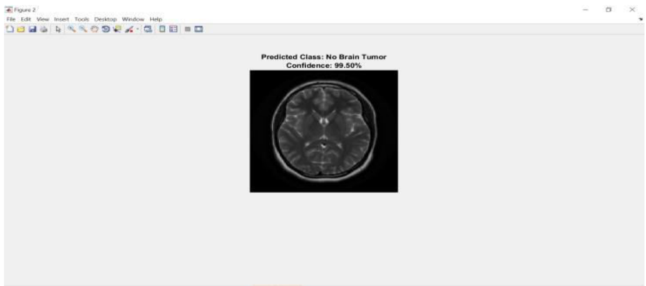

Figure 11: Output Prediction

The output image (Figure 11) shows the CNN model prediction for the given brain MRI scan. The model classified the image as No Brain Tumor with a confidence of 99.50%, indicating a very high probability of tumor presence. This result demonstrates that the CNN successfully detected normal features in the MRI image.

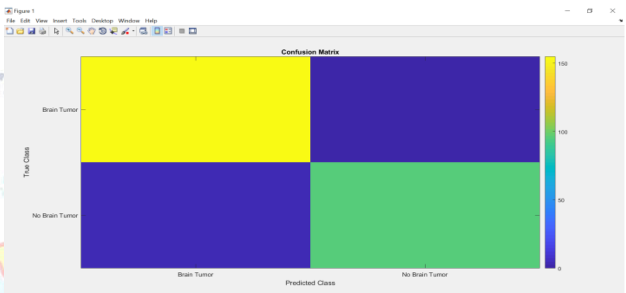

Figure 12: Confusion Matrix

A **confusion matrix**(Figure 12) is used to evaluate the performance of the CNN classification model. It shows the number of correct and incorrect predictions for **Brain Tumor** and **No Brain Tumor** classes by comparing the true labels with the predicted labels.

5. CONCLUSIONS

This work presents a MATLAB-based deep learning framework for automated brain tumour detection and classification using MRI images. The proposed system integrates preprocessing, data augmentation, and a Convolutional Neural Network (CNN) designed with batch normalization, large convolutional filters, max-pooling, and zero-padding to enhance feature extraction and improve model stability. The dataset was carefully divided into 1,445 training samples, 310 validation samples, and 310 testing samples to ensure balanced learning and minimize over fitting. The developed CNN model demonstrated strong generalization capability, achieving 91% validation accuracy and 89% testing accuracy, with F1-scores of 0.91 and 0.88, respectively. MATLAB's Deep Learning Toolbox was used for training, performance evaluation, and visualization of learning curves and confusion matrices. The results confirm that the proposed approach can accurately distinguish between tumour and normal MRI scans while reducing manual diagnostic effort. Overall, the MATLAB-based system provides a reliable and efficient computer-aided diagnosis tool that can support radiologists in early brain tumour detection

Future Scope

In future work, Long Short-Term Memory (LSTM) networks can be integrated with the CNN-based brain tumor detection system to improve feature learning from sequential MRI slices. While CNN extracts spatial features from individual images, LSTM can capture temporal and contextual relationships between consecutive MRI slices. This hybrid CNN–LSTM model can enhance tumor boundary consistency and improve classification accuracy. The approach is especially useful for 3D MRI scan analysis and tumor progression monitoring. Integrating LSTM in MATLAB using the Deep Learning Toolbox can lead to a more robust and clinically reliable brain tumor detection system.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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