Enhanced Brain Tumor Detection and Classification in MRI Scans using Convolutional Neural Networks

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***Abstract*—Tumor detection is one of the most critical and challenging tasks in the realm of medical image processing due to the risk of incorrect prediction and diagnosis when using human-aided categorization for cancer cell identification. Data input is an intensive process, particularly when dealing with a low-quality scan image, due to the background, contrast, noise, texture, and volume of data; when there are many input images to analyze, the task becomes more onerous. It is difficult to distinguish tumor areas from raw MRI scans because tumors pose a diverse appearance and superficially resemble normal tissues, which makes it more difficult to detect tumors. Deep learning techniques are applied in medical images to a great extent to understand tumor contours and areas with high intensities in input images. For timely diagnosis and the right treatment with less human involvement, and to interpret and enhance detection and classification accuracies this automated method is proposed. This proposed work is to identify and classify tumors on 2D MRI scans of the brain. In this work, a dataset is used, inside it, there are images with and without tumors of varied sizes, locations, and forms, with different image intensities and textures. In this paper, multi-layer Convolutional Neural Network (CNN) architectures are implemented. This shows two main experiments to assess the accuracy and performance of the model. First, five-layer CNN architecture with five layers and two different split ratios. Second, six-layer CNN architecture with two different split ratios. In addition, image pre-processing and hyper-parameter tuning were performed to improve the classification accuracy. The results show that the five-layer CNN architecture outperforms the six-layer CNN architecture. When results are compared with state-of-the-art methods, the proposed model for segmentation and classification is better because this model achieved an accuracy of 99.87 percent.**

Keywords*—*Multi-layer Convolutional Neural Networks (CNNs); MRI images; tumor segmentation and classification; deep learning; learning rate

I. Introduction

Medical imaging is often used by doctors to get a better look at what's going on within a patient's body and arrive at a correct diagnosis. The classification of medical images is not only a formidable intellectual challenge but also a potentially fruitful research field in the field of image processing. Cancers in medical pictures may be difficult to detect. A difficult diagnostic problem has arisen. The importance of cancer screenings cannot be overstated. Death rates and the prevalence of brain tumors attest to the fact that cancer, whether it manifests externally or inside, is a devastating disease. Every year, doctors diagnose more than a million people with tumors. The death toll keeps climbing. In terms of cancer-related mortality in those under the age of 34, it is second only to lung cancer [1]. In their quest to locate the tumor, doctors are now adopting cutting-edge methods that only serve to make patients more uncomfortable. Computerized tomography scans (CT scans) are used to examine the human body and look for anomalies. Medical Imagination Reasoning (MRI) and the alternatives each have their advantages. There is a rising interest in the study of brain tumors, and the field of image analysis has attracted a lot of attention as a means of analyzing the vast amounts of data available in medical databases. Tools to produce visual representations and complex computational measurements are both necessary for the study of such a wide range of image types. Because of this, MRI scans may now be used to detect malignant brain tumors. This is where the value of handwriting data really shines since it greatly reduces the quantity of paper that would otherwise need to be used. Medical imaging is mostly used for therapeutic and diagnostic purposes in the human body. Thus, it contributes significantly to the development of healthcare and to the betterment of people's lives. In order, to improve the efficiency of image processing as a whole [2], the process of segmentation is vital. This is because it enables the breakdown of the image into its individual elements. We have been diligently working to isolate the tumor in the patient's brain MRIs, providing assistance to medical professionals in pinpointing the precise location of the tumor in the brain. Help is given to medical professionals in pinpointing the specific site of the tumor in the brain. Diagnosis, therapy (including surgical planning), and research all depend on this kind of careful dissection and interpretation. Radiologists, engineers, and doctors all employ medical image processing to learn more about a patient's or a population's unique anatomy. It is possible to get insight into, say, how a patient's anatomy interacts with a medical device via the use of measurement, statistical analysis, and the development of simulation models that contain genuine anatomical geometries. Neoplasm, or tumor, is the medical term for a mass of abnormally growing cells. Cancer and tumor are very different concepts [2]. There are two main subtypes that might each make up a brain tumor. In contrast to malignant tumors, which do contain cancerous cells, benign tumors do not, and vice versa.

1) Benign tumor: Benign brain tumors are caused by a disruption in the normal processes of cell division and proliferation, which results in a collection of cells that, on a microscopic level, do not exhibit the classic characteristics of cancer 0. These traits distinguish benign tumors from malignant ones: Imaging techniques such as computed tomography (CT) and magnetic resonance imaging (MRI) can identify the great majority of tumors, even benign ones. All these traits point to the fact that this tumor is benign since it develops at a modest rate, and seldom spreads to other parts of the body, which might ultimately result in death, the term "benign" may give the wrong impression about the nature of these injuries.

2) Malignant tumor: Development of Carcinoma Cancer cells is the building blocks of malignant brain tumors, which often do not have well-defined borders. The rapid development of these tumors and their ability to invade adjacent brain tissue [4] has led experts to the grim conclusion that they provide a significant risk of death. The following is a list of traits that malignant tumors have malignancy that is quickly spreading, with broad metastases in both spinal and cerebral. Malignant brain tumors are graded as either 3 or 4, whereas benign brain tumors are often categorized as 1 or 2. They usually pose a far bigger danger to human life.

Recent and reliable forecasts [5] estimate that 24,530 persons in the United States will be diagnosed with brain or spinal cord tumors in 2021. There will be 13840 men and 10690 women impacted by this. Less than one percent of the population is expected to get this kind of brain tumor at some point in their life. Roughly 85–90% of primary CNS cancers have this etiology as their root cause. This article focuses on the most common types of brain tumors in adults; however, each year 3,460 children under the age of 15 are diagnosed with a tumor in their central nervous system (CNS). Both men and women rank brain and central nervous system cancer as the ninth biggest cause of death. About 18,600 fatalities in 2021 are projected to be the result of primary brain and central nervous system tumors [6]. There were around 10,500 men and 8,100 women. Therefore, it is crucial to enhance the precision of previously proposed approaches for the advancement of medical image analysis. To summarize, several advanced methods have been introduced to address the problem associated with low image quality. Various techniques have been observed to possess durable effectiveness in improving contrast, illustrating texture intricacies, and reducing noise levels. Moreover, these techniques excessively magnify the intricate features of the images. As per the existing literature paradigms, as far as the Author's knowledge, the issue of brain tumor classification for low-quality MRI scans is yet to be set up to consider it in real-time applications. Hence, to achieve this goal in the present study, a novel technique has been proposed.

The main contribution of this research is summarized as follows:

- A robust multi-layer CNN-based system is proposed for binary-class brain tumor classification on the publicly available dataset.
- An analysis is performed on MRI data because it is one of the main sources for detecting tumors in the patient's brain to detect it.
- The repetition of this invasive method in the case of non-clear images could be avoided if the system is auto trained with deep learning techniques. To overcome such problems in medical imaging. Hence, an MRI as a data input.
- An enhanced CNN classification model is implemented to identify and classify the brain tumor and compare the `achieved accuracy and performance with the state-of-the-art approaches.

The existing framework is offered in the Section II of the paper, the background details are explained in the Section III, the suggested approach is explained in the Section IV, experimental findings and comments are presented in the Section V of the paper, and lastly, a conclusion is presented in the Section VI of the paper.

II. Literature Review

Khan et al. [7] utilized contrast to lesion area compared to the background. The 2D blue channel is selected for the construction of saliency map, at the end of which threshold function produces the binary image. In addition, particle swarm optimization (PSO) based segmentation is also utilized for accurate border detection and refinement. Few selected features including shape, texture, local, and global are also extracted which are later selected based on genetic algorithm for identifying the fittest chromosome. Hussain et al. [8] devised a way to identify and measure brain tumors using MRI images. The algorithm can identify and eliminate any size, location, or form of tumor. MRI pictures are grayscale first. The blurred picture is then merged with the original. Median filters reduce noise. Dilation and erosion compute morphological gradients. A picture is improved with a morphological gradient and filter. Mean and standard deviation are used to compute the threshold. Before binarization, each pixel's threshold is checked. The image is thinned, and then dilated to reattach the destroyed tumor. Comparing original and dilated photos helps eliminate Javed et al. [9] focus will be to review the optimal features which have been used in an accurate skin cancer melanoma diagnosis computer-aided system. They addressed this problem an extensive review is performed. To perform this review, they collected quality papers based on features selection and extraction for skin lesion detection. These papers are collected by two approached: (1) search by keywords and year, (2) cross-references within the papers.

Javed et al. [10] proposed to deal with under/over segmented images is proposed a region-based active contour method and low contrast skin lesion dermoscopic images handle by implementing JSEG technique. An image fusion technique is proposed on two segmented images get by apply region-based active contour and JSEG techniques. Rashid et al. [11] used a joint design that fuses both the RBAC and JSEG method for skin lesion segmentation. Design technique improved the lesion segmentation as well as deal with the failure cases. The outcomes exhibited an incredible potential by beating state-of-the-art strategies for skin lesion segmentation from thermoscopic images. The proposed method also deals with different artifacts present in the thermoscopic images. They proposed for approach low contrast images by using histograms. Ullah et al [12] proposed early detection and classification of EXs in color fundus images. An ensemble classification of exudates in color fundus images using an evolutionary algorithm based optimal features selection. Experiment performed on benchmark datasets and a real dataset developed at local Hospital. It has been observed that the proposed technique achieved an accuracy of 98% in the detection and classification of EXs in color fundus images. Sajjad et al. [13] proposed the data augmentation with various parameters and techniques to fill the gap of data and make the system noise invariant. Multi-grade brain tumor classification system, the tumor regions from the dataset are segmented through a CNN model, the segmented data is further augmented using parameters to increase the number of data samples, and a pre-trained VGG-19 CNN model is fine-tuned for multi-grade brain tumor classification. Rehman et al. [14] proposed skull masking method to identify issues. Unsupervised SVMs build and preserve patterns using this approach..

Ahmed et al. [15], which enhances calculation time. The suggested solution hasn't been tested yet. It has 86% classification and 92% cancer detection accuracy. Histograms were utilized by Liu et al. [16] segmenting brain tumors involves two modalities: FLAIR and T1. FLAIR aberrant areas were found using an active contour model. Edema and tumor tissues in aberrant locations were separated using k-means. The dice coefficient is 73.6% and the sensitivity is 90%. Nikam et al. [17] employed edge detection and adaptive thresholding to extract ROI. By using edge detection, the dataset included 102 pictures. First, images were preprocessed, and then two neural network sets underwent canny edge detection and adaptive thresholding. Two neural networks determine whether the brain is healthy or has tumors and the kind of tumor. Canny edge detection was more accurate based on the data and models. Ye et al. [18] enhanced texture-based tumor segmentation in longitudinal MRI using tumor growth patterns. This technique exploits tumor characteristics. Mean DSC LOO and three-Folder measured the model's performance. Sarkar et al. [19] presented a PNN-based LQ model. 18 MRI scans were used for testing and the remainders were used for training. Gaussian filter smoothed photos. Improved PNN cut processing time by 79%. Sharif et al[20] used probabilistic neural networks for segmentation. PCA identified characteristics and reduced high-dimensional data. Mehrotra et al. [[21] proposed a neural network for classifying MRI matrix data and conducted a comprehensive performance analysis with the assistance of deformable models and fuzzy clustering. Rehman et al. [22] separated tumors using Linknet. All seven training datasets were initially segmented in a single Link net network. They didn't examine the perspective of the images and instead created a way for CNN to automatically separate prevalent brain tumors.

Tufail et al. [23] different DL methods are used to solve both binary and multiclass classification problems to differentiate between different stages and deployed a ten-fold cross-validation approach to select the optimal set of hyperparameters for the binary and multiclass classification tasks. For the binary classification task, the performance of architecture trained using combined augmentation methods is the best while the performance of the model trained without any augmentation is found to be the worst. Other retinal diseases such as retinal detachment using fundus images deploying data augmentation methods such as elastic/plastic deformations as well as other DL-based architectures such as graph convolutional networks.

Pitchai et al. [24] automated deep learning-based Fuzzy K-means clustering segmentation approach has been developed for brain tumor segmentation. This method includes four stages. Initially, the MRI images are preprocessed using a wiener filter for noise expulsion. From the filtered images, the significant features are extricated by using the CSOA algorithm. Then, the normal and abnormal images are classified through ANN. Finally, the fuzzy K-means algorithm has been utilized on the abnormal images to segment the tumor region. This can replace conventional invasive brain tumor classification and enhances the overall classification accuracy.An efficient strategy is employed to enhance the low visual quality of MRI images. Data augmentation technique is used to achieve high classification accuracy on a small dataset, and the impact of over-fitting on classification performance is studied. An efficient and simpler object (tumor) localization method is developed, which gets the initial locations by computing multiple hierarchical segmentation using superpixels and then rank the locations according to region score, which is defined as a number of contours wholly enclosed in the located region, only the top object locations are passed for the next task. Guan et al. [25] proposed a deep neural network (EfficientNet) is employed for rich features extraction. A comparison of the proposed method with existing state-of-the-art approaches for brain tumor classification is presented. The proposed method achieved classification accuracy compared to traditional methods.

Kaplan et al. [[26] proposed two different feature extraction approaches were used to classify the most common brain tumor types; Glioma, Meningiomas, and Pituitary brain tumors; nLBP and αLBP. Brain tumor classification using modified local binary patterns - nLBP and αLBP feature extraction methods used. This work introduces an optimized deep learning mechanism; named Dolphin-SCA based Deep CNN, to improve the accuracy and to make effective decisions in classification of brain tumor classification. Kumar et al. [27] presented mechanism of deep learning; named Dolphin-SCA based Deep CNN, to improve the accuracy and to make effective decisions in classification The segmentation process is carried out using a fuzzy deformable fusion model with Dolphin echolocation-based Sine Cosine Algorithm (Dolphin-SCA). It looks at the posterior and anterior (PA) views of X-rays, therefore it can’t tell the difference between other X-ray perspectives like anteroposterior (AP), lateral, and so on. It also needs Grad-CAM (Class Activation Mapping) visualization.

Deepak et al. [28] proposed a classification system that adopts the concept of deep transfer learning and uses a pre-trained GoogLeNet to extract features from brain MRI images. Proven classifier models are integrated to classify the extracted features. The experiment follows a patient-level five-fold cross-validation process, on an MRI dataset from Figshare. They proposed system records a mean classification accuracy of 98%, outperforming all state-of-the-art methods.

Raja et al. [29] developed a brain tumor classification using a hybrid deep autoencoder with a Bayesian fuzzy clustering-based segmentation approach. Initially, the pre-processing stage is performed using the non-local mean filter for denoising purposes. Then the BFC (Bayesian fuzzy clustering) approach is utilized for the segmentation of brain tumors.

Rammurthy et al. [30] presented a fully automated deep CNN for brain tumor detection using MR images. It also proposed a Whale Harris Hawks optimization (WHHO) is employed for training the deep CNN. The proposed WHHO algorithm is designed by combining the WOA and HHO algorithms, which can be utilized for finding the optimal weights for establishing effective brain tumor detection. Here, the segmentation is performed on each input brain MRI image using cellular automata and rough set theory. The pertinent pixel of tumor regions helps to provide improved segmentation results. Advanced optimization techniques can be explored to further compute the efficiency of existing methods.

Agarwal et al. [31] proposed a new Conv2D model for cucumber disease classification with an accuracy of 93.75%, which outperforms the state-of-the-art accuracy by 8.05%. • Modified the ReLU activation function and experimentally established that it boosts the classification accuracy by 2.5% over the regular ReLU function. They proposed a segmentation algorithm to identify the diseased regions of cucumber leaf images and work out the severity of the disease. Botta et al. [32], this approach focuses only on relevant image patches from the image, making the technique fast and memory efficient. The low FPR values obtained indicate a low chance of an intact egg being classified as cracked. Thakur et al. [33] proposed to detect and classify Covid-19 disease from normal (healthy) and pneumonia patients; to check the generalizability of the method, develop a larger dataset that includes both X-rays and CTs; to achieve a higher value of performance measures for both binary as well as multiclass problems; to calculate all the performance measures and compares the different parameters of the proposed technique to those of current techniques. Despite having a great performance, it has some drawbacks. In Ullah et al. [34], a medical decision support system using malignant and benignant classes was discussed. This system is designed by median filter, CLAHE, wavelet transform, color moments and feed-forward NN. The proposed system provides results in categorizing malignant and benign MRI images.

It has been noticed from the above research that findings with the traditional machine learning (ML) techniques are not sufficient to segment and classify the brain tumor from raw MRI images. In addition, deep learning techniques outperform the accuracy of brain tumor classification effectively. However, the size of the patient's brain tumor changes periodically, which makes it hard and time-consuming to diagnose and categorize the tumor from massive imaging sets. The structural complexity of the brain makes the building of an expert system for identifying brain tumors a challenging undertaking that is plagued by several problems, including under-fitting, biased results, overfitting, and repetition of the training samples. It takes more time to complete activities like determining the infected area, segmenting, and identifying tumors from MRIs, and it is challenging to see the abnormal brain structures using standard image processing methods. The present proposal clearly put a light on the Convolutional neural network which is the backbone of every other deep neural network. Thus, authors have tried to show the working of CNN with a slight change in layers and proportions to advance the accuracy and performance to overcome the problem of accurate detection and classification of brain tumours in MRI scans (see Table I).

TABLE I. OVERVIEW OF LITERATURE REVIEW

Reference	Objective	Methods use	Outcome
Hussain et al. [8]	Identify and measure brain tumors in MRI images.	Median filters, morphological gradients, thresholding, image processing.	Noise reduction, tumor identification, size measurement.
Javed et al. [9]	Detect brain tumor malignancy.	PCA, RST, wavelets, CNN, bilateral filters, histogram equalization.	Noise reduction, feature extraction, CNN classification.
Rahim et al. [10]	Recognize tumor blocks and types.	High-pass filters, K-means clustering, neural networks.	Segmentation, classification, noise reduction.
Rashid [11]	Employ morphological approaches and filtering.	Pixel removal, thresholding, skull masking.	Tumor segmentation, pattern recognition, noise reduction.
Ahmed et al. [15]	Improve calculation time, classification accuracy.	Not specified.	Classification accuracy improvement, untested solution.
Liu et al. [16]	Segment brain tumors using FLAIR and T1 modalities.	Active contour model, k-means, edge detection, neural networks.	Aberrant area detection, sensitivity, dice coefficient.
Nikam et al. [17]	Extract ROI and classify brain tumors.	Edge detection, adaptive thresholding, neural networks.	Edge detection accuracy, tumor classification.
Ye et al. [18]	Enhance texture-based tumor segmentation.	Texture-based features, mean DSC LOO, 3-Folder, longitudinal MRI.	Texture-based segmentation, performance measurements.
Sarkar et al. [19]	Present a PNN-based LQ model.	Gaussian filter, probabilistic neural networks, PCA.	Processing time reduction, feature identification.
Sharif et al. [20]	Use probabilistic neural networks for segmentation.	PCA, neural network classification.	High-dimensional data reduction, performance analysis.
Rehman et al. [22]	Separate tumors using Linknet.	Linknet network, CNN, prevalent brain tumors.	Automatic tumor separation, CNN-based approach.
Guan et al. [25]	Improve visual quality, tumor location proposals.	Efficient-net, image-pre-processing.	Tumor segmentation in multi-modal images.
Kaplan et al. [26]	Classify common brain tumor types.	Local binary patterns, nLBP, αLBP.	Tumor type classification based on feature extraction.

Rammurthy et al [30]	Optimization employed to obtain optimized weight.	Whale Harris Hawks Optimization algorithm used	Improved segmentation, and accuracy.

III. Background

A. Convolutional Neural Network

CNN is an example of an artificial neural network, often known as a multilayered sensor. Its architecture is inspired on the structure of the visual cortex. One of the most important ideas behind deep learning is the Convolutional Neural Network or CNN. CNN consists of two basic processes, which are referred to as convolution and pooling, and is often used in applications that are related to image recognition. Additional layers of convolution and pooling are added as necessary up to the point when a high level of classification accuracy is obtained. In addition to this, certain feature maps are included in each convolutional layer, and the weights of convolutional nodes that are contained inside the same map are shared. These designs minimize the number of traceable parameters while allowing for the learning of a variety of network properties. CNN, in contrast to more traditional methods, may learn to completely extract features while simultaneously performing a reduced number of specialized duties. The whole process plan of a CNN is shown in Fig. 1.

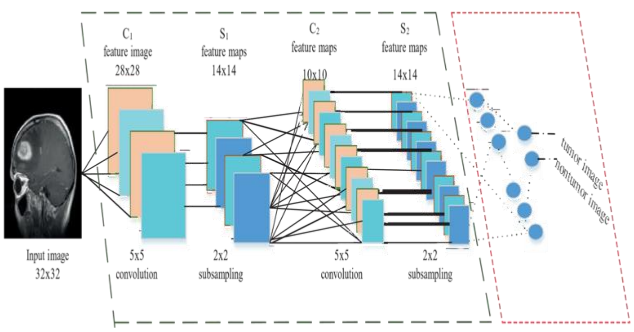

Fig. 1. CNN process.

B. Background of Tumor Detection

Preprocessing: Noise may affect MR images. Picture compression and data transfer may produce noise. Nonlocal techniques and local smoothing were used to reduce noise [. Some significant visual structures and features might appear as if they were made of noise; these vital details may also be deleted. Below figure shows axial, coronal, and sagittal MR images. Fig. 2(a) and 2(b) show an original and preprocessed image.

C. Watershed Segmentation and Morphological Process

Good cranial MRI segmentation using watershed segmentation. This method detected cancer. Geography and water supply basins determine watershed lines. It analyses grey data and determines the object's boundaries by using the topological structure of the object inside an image. It enhanced the submerge-based watershed transformation method. It's lowest and maximum values are hmin and hmax. Moving from hmin to hmax shows recursion. Xh basin clusters were comparable to dot clusters with hmin at recursion's start. The Xh basin cluster in the threshold cluster eventually grows.

$$Xh = \min \cup \; IZTh + 1(f)(Xh), \forall h \in [hmin\, , hmax - 1] \quad (1)$$

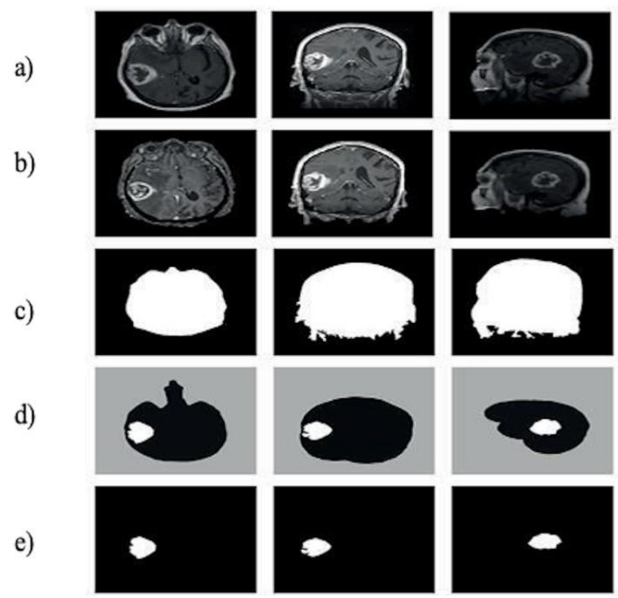

Fig. 2. (a) Original image, (b) Pre-processed image, (c) Segmented skull image, (d) Brain tissue extraction, (e) Tumor detection.

First, the program collects gradient data. Subtracting the first derivative of pixel change yields this data. Next-level activation requires the signal. Image segmentation requires pointer pixels for each class. These pixels' location and quantity affect segmentation success. The watershed transformation has interesting features for mathematical morphology image segmentation. This change is intuitive. It generates closed curves quickly. Over-segmentation is a nearby one fused, and gaps were filled. Fig 2(c) shows how watershed segmentation eliminates data from MR images. Fig. 2d shows how the brain's soft tissue was created by removing the skull from the original image. Fig 2(e) shows how morphological segmentation and classification of brain tumour in MRI scans and assist the radiologist.

IV. Proposed Work

The proposed five-layer CNN model can identify a tumor in MRI images. Fig. 3 shows the five-layer CNN technique. Firstly, load the input dataset with the same-sized images. Five-layer CNN is used for early identification of tumors and a model includes seven steps (eight if you include the hidden layers), yielding the best results for tumor detection and splitting down the process into seven steps from which a brain tumor may be detected utilizing CNN. Step-by-step instructions shown below reveal the process. In Fig. 4, the proposed method for tumor detection using a five-layer Convolutional Neural Network is shown. Five discrete dimensions are also used.

A. Convolutional Layer

A convolutional layer is CNN's backbone. First, a convolutional layer is used to resize MRI images. This makes a 64*64*3 input shape. After gathering all same-orientation input images developed a convolutional kernel using 32 3*3 convolutional filters and three channel tensors. The activation function is ReLU. The filter size is three times the 64x64x3 input volume.

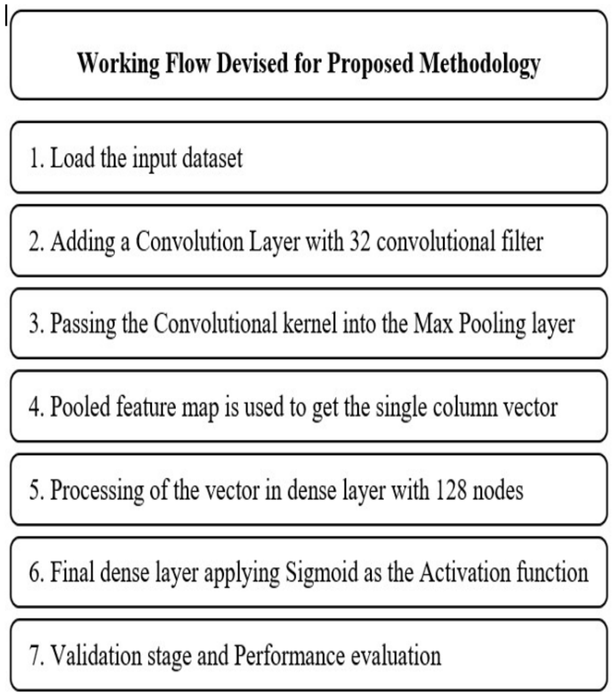

Fig. 3. Five layer CNN model workflow.

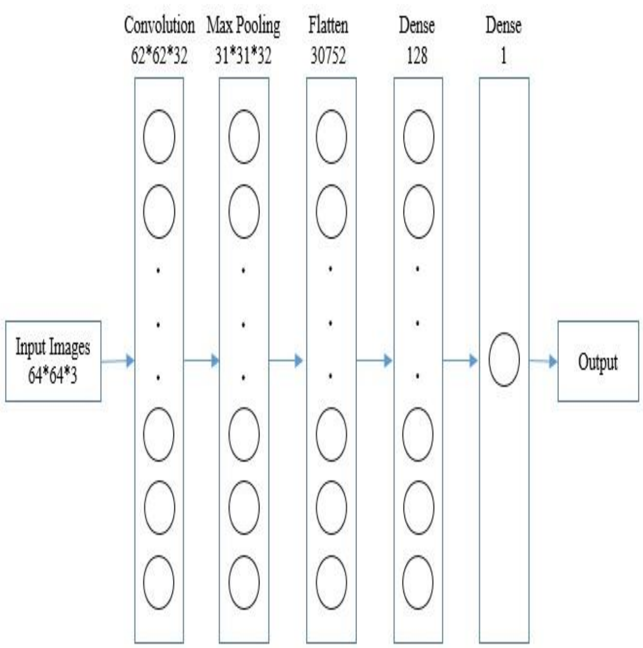

Fig. 4. Five-layer CNN for brain tumour detection.

Each neuron in the convolutional layer has 3*3*3 = 27 weights, plus one for the bias parameter. Assess depth, stride, and zero-padding. The model contains a 64*64*3 input volume and a 33 spatial filter. Since it didn't specify border padding, padding and stride are both 1. If the stride is set to 1, only the pooling layers will down sample; the CONV layers will alter the input volume in depth. After the convolutional layer, added max pooling.

B. Max Pooling Layer

The fundamental objective of the pooling layer is to reduce the number of parameters and computation workloads in the network by progressively decreasing the spatial size of the representation. Over-fitting may be managed thanks to its ability to scale down the settings. The max pooling layer may be used to enlarge the input spatially, and it can do so on a per-slice basis if the input is deep enough. From another angle, the Max Pooling layer is great for preventing over-fitting, which might introduce contamination into the brain MRI image when editing it (see Fig. 5). Therefore, MaxPooling2D (see Fig. 6) check the effect of the pooling operation as a pre-processing step which was used on the input image. There are a total of 32 nodes in this convolutional layer, resulting in a 31*31*31 matrix.

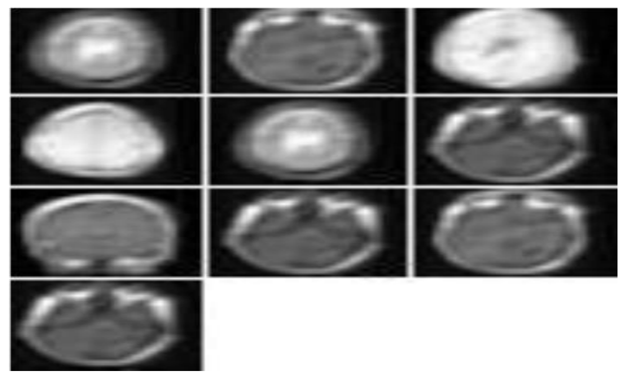

Fig. 5. CNN operation unit.

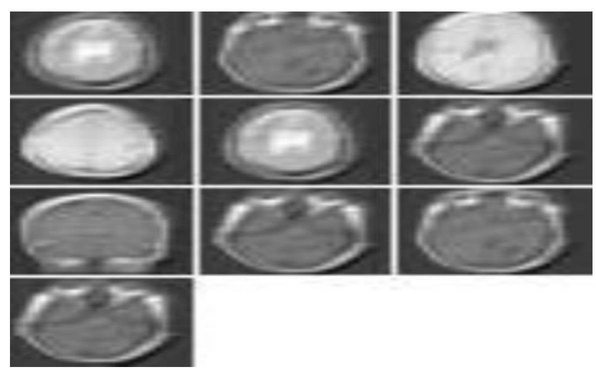

Fig. 6. Pooling operation unit.

C. Flatten Layer

Pooling creates a pooled feature map that extracts necessary features only and discards unimportant features refer to Fig. 6. The flattened layer is crucial after pooling because it transforms the input's feature maps into a single-column vector for processing. The neural network processes it as Layer 31*31*32 = 30752 pixels.

D. Fully Connected Layer

The dense-1 and dense-2 (see Fig. 7) layers were linked. Keras processes the neural network using the dense function, and the output vector is fed to this layer. Each layer has 128 nodes. Due to high processing costs, the number of dimensions or nodes is 128. ReLU is employed due to its high convergence. The model's final layer was the second totally linked layer, utilizing the sigmoid function as the activation function in this layer with one node to reduce execution time. Sigmoid activation may impair deep network learning. The sigmoid function has been lowered, reducing the number of nodes in this deep network.

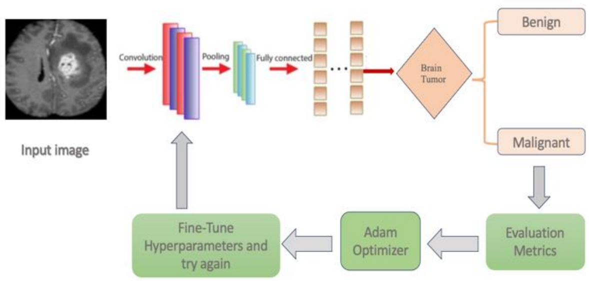

Fig. 7. Proposed model workflow.

V. Results and Discussion

A. Experimental Setup

Jupyter Notebook and Python technologies like NumPy, Pandas, and OpenCV were used for image processing. For classifiers, use Scikit-Learn, Anaconda and Python 3.6.

CNN model was trained and tested using TensorFlow and Keras used Google Colab's GPU.

B. Dataset Acquisition

Br35H-Mask-RCNN dataset [16] is used to segment brain tumors. Cancers and non-tumors are labeled. A set has two classes. Class-1 is tumors MRI while Class-2 is non-tumors (class-0). Training is 700, testing is 100 and 24 images test performance.

C. Performance Measures

To assess how well the proposed model works, one must consider performance metrics. Below is the discussion on the proposed model's performance statistics. One must learn performance measurement lingo to understand the Confusion Matrix.

Confusion Matrix:

TP: Number of correctly identified tumor images.

TN: The number of correctly detected non-tumor images.

FP: The number of non-tumor images labeled tumor.

FN: Number of tumor images misclassify as non- tumor.

Accuracy: It's the most common way to measure how often a classifier is correct. Accuracy is the ratio of accurately predicted images to the total number of photos.

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (2)$$

Precision: The model's data is retrieved. Precision is the ratio of correctly detected tumor images (TP) to misclassified ones (TP+FP). Precision rises with FP. A more accurate model is more effective. It's the proportion of retrieved images.

$$Precision = \frac{\text{TP+TN}}{\text{TP+FP}} \quad (3)$$

Recall: Recall is the ratio of tumor photographs correctly detected to images to be projected. It's also called sensitivity, hit rate, and true positive rate. Because non-tumor images are rare, a smaller false negative increases memory.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

F-Score: The harmonic mean of recall and precision is used as a measurement of test accuracy. F-scores range from 1 (perfect accuracy and recall) to 0 (zero).

$$\text{F} - \text{Score} = \frac{\text{2TP}}{\text{2TP+FP+FN}} \quad (5)$$

Specificity: Specificity is the F-Score. The model's True Negative Rate (TNR) and binary classification test's statistical measure is specificity. Use this as a performance evaluation as it's binary (tumor or non-tumor). The ratio of correctly identified non-tumor images (TN) to wrongly categorized non-tumor images (TN + FP). The more specificity, the fewer false positives (FP).

$$Specificity = \frac{\text{TN}}{TN+FP} \quad (6)$$

D. Experimental Results

The five-layer CNN model got the best results for splitting ratio and other parameters. Then split CNN model performance by layer count. Next, is presented the experimental results and quality and evaluation. Experiments I and II tested the five-layer model with 70:30 and 80:20 learning rates and epoch-splitting ratios. Later, it is examined as five, six, and seven-layer CNN models.

1) Experiment-I: The five-layer CNN model is trained using 70 by 30 ratios. Table II shows how this ratio impacts learning rate, epochs, training length, and accuracy. The highest accuracy was attained using a 0.001 learning rate, 50 epochs, and 500 seconds of training.

TABLE II. CNN Training Time Accuracy (Splitting Ratio of 80:20)

Learning Rate	Time	Time to train(sec)	Accuracy (%)
0.001	10	175	99.51
	20	233	98.87
	50	527	95.74
	100	1200	95.69
0.005	10	177	96.03
	20	203	97.62
	50	488	95.55
	100	1027	95.55
0.01	10	178	92.09
	20	200	93.04
	50	599	93.77
	100	966	92.00

2) Experiment – II: The five-layer CNN model is trained using 80 by 20 ratios. Table III compares training, accuracy, learning rate, and epochs. The greatest accuracy is 99.51 percent at a 0.001 learning rate and 10 epochs, and training takes 175 seconds.

TABLE III. CNN TRAINING TIME ACCURACY (SPLITTING RATIO OF 70:30)

Learning Rate	Time	Time to train(sec)	Accuracy (%)
0.001	10	180	98.66
	20	231	98.95
	50	500	99.58
	100	1227	96.01
0.005	10	198	98.18
	20	240	99.13
	50	555	97.68
	100	1133	97.22

3) Experiment-III (Five-layer Architecture): This analysis used several hyper-parameters and splitting ratios to test the five-layer CNN model. Table IV compares 80:20 and 70:30 five-layer CNNs. The model is most accurate for 80:20, 64, and 10 epochs. The model overfits thereafter. Five-layer CNN accuracy is 99.87%.

TABLE IV. CNN PERFORMANCE FOR FIVE LAYERS

Convolution Layer	Coalescing	Fracture Percentage	Group Measurement	Time	Accuracy (%)
62*62*32 62*62*32 (2 layer)	31*31*32	80:20	32	8	89.29
				9	92.83
				10	93.76
				11	93.62
			64	8	94.01
				9	96.08
				10	95.49
				11	94.21
		70:30	32	8	82.37
				9	83.71
				10	84.24
				11	86.17
			64	8	88.27
				9	82.23
				10	81.69
				11	80.07

4) Experiment-IV (Six-layer Architecture): Add 62*62*32 convolutional layer. Changing model dimensions may affect accuracy. Table V demonstrates 80:20 splitting, 64 batches, and 11 epochs. Model accuracy deteriorated. . Convolutional layers don't improve accuracy. Two kinds of CNN models were employed for the suggested model, and the five-layer CNN model had 99.87% accuracy. Table VI compares an CNN models from trial III and IV.

TABLE V. CNN PERFORMANCE FOR SIX LAYERS

Convolution Layer	Coalescing	Fracture Percentage	Group Measurements	Time	Accuracy (%)
62*62*32	31*31*32	80:20	32	8	99.87
				9	99.77
				10	99.51
			64	8	93.67
				9	94.98
				10	97.87
				11	94.89
		70:30	32	8	81.35
				9	83.71
				10	87.87
				11	89.13
			64	8	88.07
				9	88.76
				10	91.23
				11	94.90

TABLE VI. COMPARISON OF CNN MODELS

No. of Layers	Convolutional Layer	Coalescing	Fracture Percentage	Group Measurements	Time	Accuracy ((%)
5	62*62*32	31*31*32	80:20	64	8	99.87
6				64	9	96.08

E. Discussion

The proposed method uses a pre-processing, data augmentation, convolutional kernel, filter, and three channel tensors added in the process to improve classification. Techniques like MaxPooling2D were used to reduce the overfitting problem and added two fully connected dense layers with ReLU as an activation function.

A detailed discussion on the effect of execution time, variation in proposed results, and comparison with different add or removal of layers in CNN are projected here. The process is implemented on two different architecture styles and measures the accuracy and system computational time, such as 80:20, and 70:30 on five-layer CNN architecture which can be viewed from Table II and Table V. In these tables, it is shown that the best-achieved accuracy is 99.87%, 99.77%, 99.51% etc. The variant performance of the proposed methodology is noticed when we add or drop the classifier layers and training proportions on the proposed model. The proposed selected features are best for five-layer CNN. Also, applied hyperparameter tuning on six-layer CNN. However, the results are not up to the scale (see Table V) when compared with five-layer CNN, 80:20 training split ratio (see Table IV) and observed that this method improves the computational and classification accuracy.

List of Hyperparameters used in this study are Batch size, Learning Rate, number of epochs, number of filters, kernel size, pooling size. Refer to Table II and Table III to check tuning performance of proposed model. In addition, Adam optimizer is used. The above parameters can fine-tune each time we find less accuracy as per the evaluation metrics see Fig. 7. To evaluate the proposed model plotted confusion matrix (See Fig. 8)

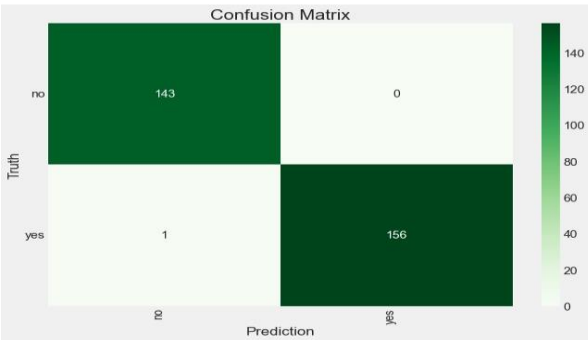

Fig. 8. Confusion matrix.

VI. Conclusion and Future Works

In this analysis, the enhanced tumor segmentation and classification from MR images is presented. The proposed model used two techniques with CNN which works in two phases: (1) five-Layer CNN with Hyper-parameter tuning; (2) six-layer CNN with hyperparameter tuning with various data training proportions. This model performed well because of 2D Max pooling, ReLu activation function and used Adam as optimizer and fine tune with batch size, learning rate. In a proposed approach, the best features selection step not only increases the accuracy but also minimizes the classification time. However, this study has limitation for computing large datasets and complex CNN's this model may not give same accuracy to other datasets. In the future, we aim to extend our current work for fine-grained classification of multi-modal MRI images on advanced CNN architectures like R-UNet and aim to use a high-performance computational platform for the complete dataset for further improvement in segmentation feature map and classification. This soon can be deployed in real-time applications in a broader prospect.

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