International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Employing CNN Features for Automated Brain Tumor Classification in MRI

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Submitted: 05/11/2023 **Revised**: 25/12/2023 **Accepted**: 04/01/2024

Abstract: Brain tumor is a rapid growth of nerves cell ultimately it form a mass of cell. Tumour found in any part of brain. Finding the proper position of tumor is sometime very difficult task. This problem is solving by deep learning techniques. Deep learning is a neural architecture and learns from data. It is a mostly cause of death all around the world. So proper solution to this problem is required. This research focused on diagnoses tumours in early stage, using an innovative approach to improve the accuracy and efficiency of brain tumor detection using Convolutional Neural Networks (CNNs). This model objective is to identifying abnormal images and segmenting the tumor region using multi-level thresholding. This segmentation aids in estimating tumor density for treatment planning. By leveraging deep learning and advanced image analysis, it aims to create a reliable and automated system for brain tumor detection.

Keywords: *CNN, Deep Learning*

1. Introduction

Now a day, significant advancements in medical imaging have sparked a revolution in the determination and treatment of various diseases. Among these advancements, the field of brain tumor analysis has emerged as a particularly challenging and vital area. Brain tumors can severely impact a patient's cognitive abilities, motor skills, and overall quality of life, underscoring the critical importance of early and accurate detection for improved medical interventions and patient outcomes.

Traditionally, radiological imaging techniques like computed tomography (CT) and magnetic resonance imaging (MRI) have been the go-to methods for diagnosing brain tumors. These modalities provide high-resolution images that offer valuable insights into the brain's structure and any pathological conditions. However, the interpretation of these images demands considerable time and expertise from radiologists.

To address these challenges, the combination of deep learning and image processing has emerged as a promising approach in brain tumor analysis. Deep learning, a subset of artificial intelligence, has demonstrated its ability to automatically extract features, identify patterns, and classify data effectively. When applied in conjunction with specialized image processing techniques tailored for medical imaging, deep learning algorithms have the strength to significantly enhance the speed and precision of brain tumor diagnosis.

In the context of this research study, overall aim is to explore and showcase the potential of deep learning and image processing approaches in the analysis of brain tumors. We will delve into the major challenges encountered in this field, such as the variability in tumor sizes and shapes, the presence of noise in medical images, and the need for real-time analysis.

Furthermore, these research findings hold substantial implications for the development of personalized treatment strategies. By employing deep learning models capable of recognizing specific tumor characteristics and biological markers, clinicians can tailor treatment regimens to individual patients. This paves the way for precision medicine, where treatments are finely tuned to match the unique biology of each patient's tumor, ultimately improving treatment effectiveness while minimizing adverse effects and undesirable responses associated with standard treatments. It is important to note that as we advance, we must also address ethical considerations and data security concerns.

This study underscores the vital importance of collaboration between the fields of medicine and computer science to effectively harness the strength of deep learning and image processing in brain tumor analysis. Radiologists, neurologists, data scientists, and engineers must work together to develop, validate, and implement these technologies in clinical settings. Bridging the gap between cutting-edge research and practical patient care demands seamless communication and knowledge-sharing among diverse fields.

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In conclusion, our study embarks on a quest to unlock the transformative possibilities of deep learning and image processing in the realm of brain tumor analysis. Our vision is to pave the way for a future where brain tumor diagnosis and treatment are not only more accurate but also more compassionate and inclusive, achieved through rigorous testing, ethical considerations, and a steadfast commitment to patient-centric care.

2. Literature Review

Various methods and procedures from various research studies have been thoroughly studied and some of them are mentioned below:

Marcin Woz´niak, Jakub Siłka, and Michał Wieczorek introduced a novel correlation learning mechanism (CLM) in their research paper [1], which combines a convolutional neural network (CNN) with a classical architecture. The integration of a supporting neural network aids the CNN in identifying the most appropriate filter for compression and convolution layers. Consequently, the fundamental neural classifier exhibits accelerated learning and attains heightened efficiency. The CLM model demonstrates a precision of approximately 96% and a precision and recall of around 95%. Notably, the proposed CLM model exhibits rapid learning capabilities from data. It is evident that all metrics indicate the model's capacity for swift and effective learning. This system offers a fresh and accessible comprehension of CNN composition [9-17].

Emrah Irmak [2] introduced three distinct CNN models tailored to three separate classification tasks. The initial CNN model demonstrated a remarkable 99.33% accuracy in detecting brain tumors. The second model successfully categorized brain tumors into five specific types: glioma, meningioma, pituitary, and metastatic, achieving an accuracy of 92.66%. Meanwhile, the third CNN model effectively classified brain tumors into three distinct classes—class II, class III, and class IV—with an accuracy of 98.14%. Notably, all pivotal hyperparameters of the CNN models were automatically determined through the implementation of a network search optimization algorithm [10,18].

Saurabh Kumar [3] ,et al introduced an automated diagnostic approach for detecting brain tumors through image processing. Building upon established methodologies for brain tumor segmentation and detection in MRI brain imaging, their project showcased an impressive overall accuracy of 97%. Additionally, they highlighted the utilization of a unique weight addition to the filter within the CNN layer as a research tool. This strategic enhancement enables precise regulation of the filtering process, resulting in a more comprehensive depiction of crucial image objects in the feature map. Consequently, this refinement has the potential to enhance the overall statistics of the Artificial Neural Network (ANN) [11,19].

Priyanka Bedekar [4] et al, emphasized the significance of image recognition and segmentation in the process of brain tumor detection. They implemented fourth-order partial differential equations to eliminate noise, employed histogram equalization for image enhancement, and utilized morphological operators, namely erosion and dilation, for border removal. Notably, they opted for a fitting threshold approach instead of a global threshold for segmentation. However, a significant drawback highlighted in their research pertains to the complexities associated with MRI-based tumor staging, which often proves challenging, imprecise, and time-consuming, requiring the expertise of seasoned radiologists. The presence of diverse tissue structures within MRI images occasionally results in ambiguous features, complicating the decision-making process [12,20].

Ajesh Shermin et al [5], introduce a novel system for the classification of brain tumors. Especially, their proposed system achieved an impressive accuracy rate of 92.31%. The research paper outlines a methodology for categorizing brain MRI images that incorporates advanced machine learning techniques and comprehensive brain structure analysis. This approach facilitates the precise identification and delineation of isolated brain regions, thereby enhancing the accuracy and detection of the Region of Interest (ROI) in question. The study advocates a hybrid approach for MR brain tumor recognition, combining the utilization of DWT transformation for feature extraction, genetic algorithms for feature reduction, and the employment of Support Vector Machine (SVM) for brain tumor classification. Various segmentation techniques, such as region-based segmentation, edge-based techniques, and thresholding, are proposed for the identification of cancerous cells from normal cells. Additionally, the paper discusses common classification methods, including Neural Network Classification, SVM Classification, and Decision Classification [13,21].

Heimans et. al [6] emphasize the significance of measuring Health-Related Quality of Life (HRQL) in comprehending the disease burden and evaluating the efficacy of specific tumor treatments. Quality of life, being a multidimensional construct, encompasses various aspects such as physical, psychological, and social phenomena. To facilitate this assessment, numerous tools for evaluating quality of life have been developed. Widely used general HRQL instruments include the European Organization for Research and Treatment of Cancer Quality of Life Questionnaire (EORTC QLQ-C30) and the MOS Short Form Health Survey. Additionally, the Brain Tumor Specific Scale serves as a supplementary brain cancer module designed for use in conjunction with the general questionnaire. The paper presents the utilization of HRQL measurements and neuropsychological tests to investigate the impact of radiotherapy and surgery on low-grade glioma patients, as well as the effects of tumor size, tumor location, performance status, and age on both low-grade and high-grade glioma patients [14].

Heba Mohsen [7] et al, discuss the application of Discrete Wavelet Transform (DWT) in segmenting brain MRI into normal and various types of malignant brain tumors, including glioblastoma, sarcoma, and metastatic bronchogenic carcinoma. The new methodology's architecture shares similarities with the convolutional neural network (CNN) structure but necessitates fewer hardware resources, resulting in improved processing time for large-scale images (256x256). Furthermore, the implementation of the Deep Neural Network (DNN) classifier demonstrates significantly higher accuracy in comparison to conventional classifiers. The promising outcomes achieved through the utilization of DWT can serve as a valuable foundation for future research in conjunction with CNN, thereby facilitating a comparative analysis of the results [15].

Febriantol et al, [8] demonstrate the capability of convolutional neural networks in identifying brain tumors within MRI images. The study achieves an impressive accuracy rate of 93% alongside a minimal loss value of 0.23264. The study highlights the significant impact of the number of convolutional layers on classification quality, indicating that an increased number of convolutional layers can enhance accuracy results, albeit at the cost of extended training time. Implementing image augmentation techniques further contributes to refining the selection of existing databases and improving overall classification outcomes. In conclusion, the study emphasizes the ongoing need for research focused on CNN-based brain tumor detection to optimize the model's performance and ultimately enhance patient outcomes [16].

3. Methodology

This research comprises several key components, including image acquisition, pre-processing, segmentation, feature extraction, and classification.

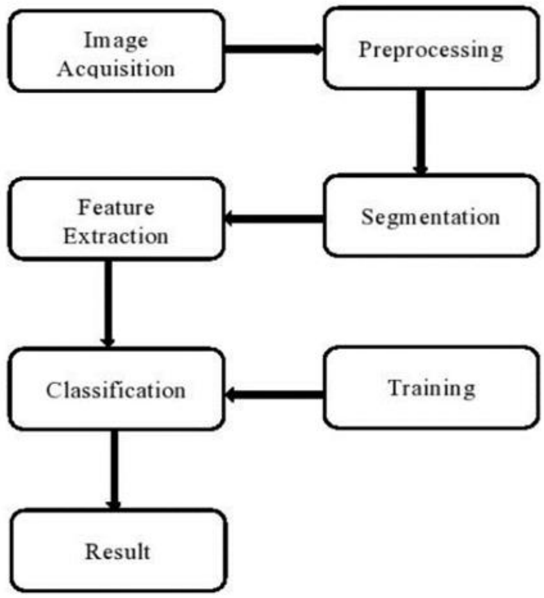


Fig. 1: Workflow of the proposed system

3.1 Image acquisition

Numerous biomedical related image records are available for the study of brain tumor detection, with traditional methods encompassing CT and MRI. Moreover, advanced methodologies like Positron Emission Tomography, Cerebral Arteriogram, Lumbar Puncture, and Molecular testing are implemented, although they entail higher costs, in the course of brain tumor detection. MRI operates based on the principle that magnetic fields and radio waves can generate internal images of the human body by detecting water molecules within its structures. To overcome the complexities associated with conventional scanning methods, portable and miniaturized MRI machines have been developed. MRI offers superior resolution and provides comprehensive information.

For this study, the MRI dataset uploaded by Navoneel Chakrabarty on Kaggle has been utilized. In this particular dataset, the label 'yes' indicates tumor images, while 'no' indicates healthy images. To expand the dataset and enhance the sample size, multiple techniques have been implemented, encompassing a rotation range of 10 degrees, width shift range of 0.1, height shift range of 0.1, brightness range of (0.3,1.0), and horizontal and vertical flips.

3.2 Pre-processing

The primary goal of the pre-processing stage is to ready the brain images for subsequent processing, a task heavily reliant on the unique parameters of the data acquisition device. If the raw data is in 3D, conversion to either a gray scale or 2D format becomes essential. To address noise in biomedical images, median filtering emerges as the most suitable approach. Given the dataset's diverse resolutions, each image is standardized through rotation and scaling during the augmentation process. Furthermore, histogram equalization is utilized to enhance image quality, with the implementation of the contrast-limited adaptive histogram equalization algorithm specifically selected for improving the images.

3.3 Image Segmentation

In this step, a digital image is divided into multiple segments to isolate a specific region from the background. This segmentation process is crucial for subsequent feature extraction. Thresholding and morphological operations such as erosion, dilation, and opening are simple techniques commonly employed for disease segmentation. However, when dealing with brain tumor images, segmenting at this level may not provide sufficient details regarding tumor regions. Additionally, healthy images can exhibit intensity patterns that resemble tumor regions, further complicating the segmentation process.

In response to this challenge, the segmentation process can be employed to isolate the skull region of the brain, containing the Region of Interest (ROI) harboring the tumor. An OTSU-based thresholding algorithm is applied to derive a segmented mask of the skull. Additionally, the active contour method is utilized to define the boundary of the enclosed region. During the second stage of segmentation, supplementary processing can be applied to the ROI to create a mask tailored for the tumor region. However, it is crucial to acknowledge that this method might not yield precise outcomes for healthy images.

The segmented image obtained can then be utilized to study the features of the tumor region, aiding in the estimation of density and further analysis.

3.4 Feature extraction

Analysing the computed features can provide insights into the behaviour and symptoms of the disease. The selection of appropriate features plays a significant role in the classification process. Some commonly used features include asymmetry, diameter, and border irregularity. These features can help distinguish between different types of tumors and contribute to accurate classification.

Fig. 2: Segmented tumour region using multiple thresholding

3.5 Classification

Various machine learning approaches are being employed for disease detection from brain images. Artificial neural networks (ANNs) can be utilized for classification when features are extracted in a specific order. ANNs assume that each feature is independent of the others.

Deep learning techniques, on the other hand, can be highly effective in classifying tumor images without the need for explicit segmentation. A deep neural network using the Convolutional Neural Network (CNN) algorithm can be constructed. The general architecture of a CNN is depicted in Figure 6. In deep learning, features are automatically extracted from the entire image, and this is achieved through the convolution operation in the CNN architecture. The number of feature maps increases as the number of convolutional layers (CONV layers) increases. To facilitate training, dimension reduction is necessary. This is achieved through pooling layers, which downsample the feature dimension. Fully connected layers manipulate the scores assigned to each label, and SoftMax layers prepare the model by incorporating the extracted features and class scores. The CNN architecture is slightly modified in its dimension for training the brain tumour images

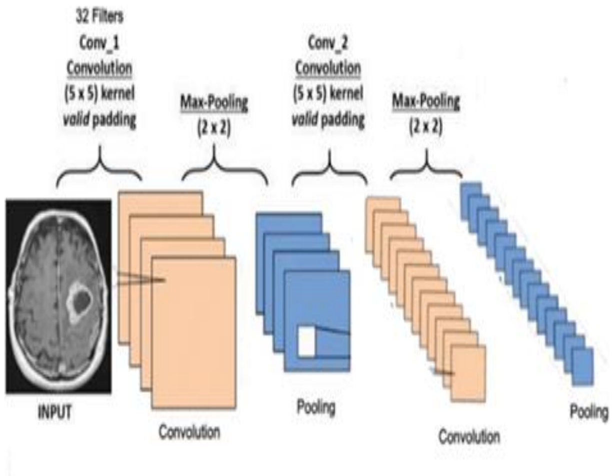


Fig. 3: Architecture for CNN Model

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 220, 220, 32)	2432
max_pooling2d (MaxPooling2D)	(None, 73, 73, 32)	0
conv2d_1 (Conv2D)	(None, 71, 71, 32)	9248
max_pooling2d_1 (MaxPooling2	(None, 35, 35, 32)	0
conv2d_2 (Conv2D)	(None, 33, 33, 64)	18496
max_pooling2d_2 (MaxPooling2	(None, 16, 16, 64)	0
flatten (Flatten)	(None, 16384)	0
dense (Dense)	(None, 512)	8389120
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 128)	65664
dense_2 (Dense)	(None, 2)	258

Total params: 8,485,218
Trainable params: 8,485,218
Non-trainable params: 0

Fig. 4: Model Working

The process of constructing this model involves several sequential steps. Initially, we utilize the Sequential model from the keras library to establish the foundation. Subsequently, we incorporate layers to formulate a Convolutional Neural Network (CNN). In the first two Conv2D layers, we employ 32 filters with a kernel size of (5,5).

Within the MaxPool2D layer, we set the pool size to (2,2), indicating that it selects the maximum value from each 2 x 2 region of the image. This operation reduces the image dimensions by a factor of 2. In the dropout layer, a dropout rate of 0.25 is applied, resulting in the random removal of 25% of neurons.

These three layers are repeated with some parameter adjustments. Following this, a flatten layer is introduced to transform the 2-D data into a 1-D vector. Subsequently, a dense layer is added, followed by another dropout layer and a final dense layer. The last dense layer generates 2 output nodes, signifying the presence or absence of a brain tumor. It employs the SoftMax activation function, which assigns probability values to each option and selects the one with the highest probability.

The Keras model is compiled using the 'Adam' optimizer and 'Binary cross entropy' loss function, with a default learning rate of 0.001. The training process employs a batch size of 32 and continues for 24 epochs. During testing on new images, the trained model achieves an accuracy of 95.6%. The model is then compiled and applied using the fit function, with a batch size of 2. Subsequently, accuracy and loss graphs are plotted.

To identify and isolate the specific regions within images that contain a brain tumor, a series of image processing techniques are applied. These techniques involve multilevel thresholding, morphological operations, contour extraction, and density estimation.

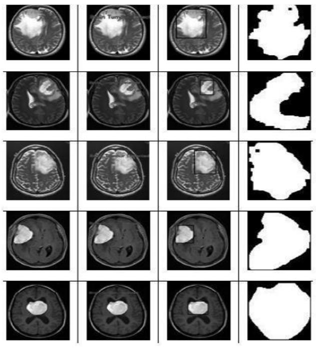
$$g(x,y) = \begin{cases} 1, f(x,y) > T \\ 0, f(x,y) \leq T \end{cases}$$

Let T represent the average of the Maximum to Minimum intensities within the image. The segmentation process employs the Morphological Open function to isolate the regions of interest. Following this, the contours of all identified regions are delineated, and the tumor region is identified as the area with the maximum extent.

The Density of the tumour area can be estimated using Gaussian kernel distribution.

$$f(x) = \frac{1}{n\sigma\sqrt{2\pi}} \sum_{i=0}^{n} e^{-\frac{1}{2}(\frac{xi-x}{\sigma})^2}$$

4. Result



Tumor Detection Result

(a) Input Image

(b) Abnormal detection

(c) Tumor region Detection

(d) Tumor mask for density estimation

(a) (b) (c) (d)

Fig. 5: Tumor Detection Result

The proposed system aims to classify malignant brain tumors using MRI images. Many MRI images were obtained from the Kaggle database. However, this amount of data is not enough to build a deep neural network model. To solve this problem, the multiplication method is used to generate 10x times images. The shape of the extracted piece is then transformed to the (240, 240) axis.

The model was developed using the keras framework and the TensorFlow framework. To evaluate the performance of the system, two-level segmentation is performed at different levels. Segmentation is performed before and after classification, and the results of segmentation after classification show superior results based on performance analysis.

This algorithm shows faster performance for conventional MRI images. If it detects an abnormal image, it moves on to the next step, which involves segmentation. The ROC curve provides a visual representation of the algorithm's performance, showing the relationship between sensitivity and specificity. At the end compared the model with already available system and proposed method give better result i.e. 98%.

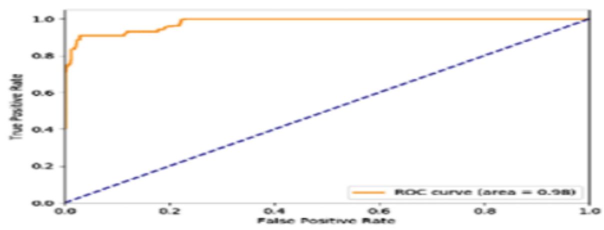


Fig. 6: ROC plot for normal cases:

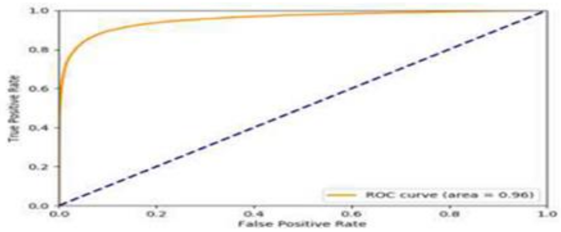


Fig. 7: ROC plot of Abnormal cases:

For our modified approach, the result parameters are:

Accuracy = (TP+TN)/(TP+TN+FP+FN) = 0.96

Sensitivity = TP/(TP+FN) = 0.95

Specificity = TN/(TN+FP) = 0.96

Where ,

TP- True Positive

TN-True Negative

FP-False Positive

FN-False Negative

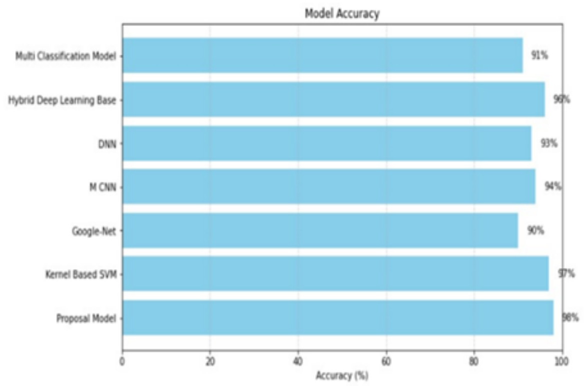


Fig. 8: Comparison of Accuracy Scores of the proposed model (Model A) with the existing models

5. Conclusion and Future Scope

The brain tumor detection using CNN algorithm has the potential to revolutionize the early detection and treatment of brain tumors. Brain tumors are difficult to detect, and early detection is crucial to prevent serious health complications. In this manuscript CNN algorithm was developed by processing a large dataset of MRI scans through several layers of filters to extract features and patterns that are characteristic of brain tumors. The algorithm has been trained to accurately detect the presence of a tumor in the MRI scan. Early detection of brain tumors is critical, as it allows for prompt medical intervention and increases the chances of successful treatment. Early detection can also lead to a better quality of life for patients and reduce healthcare costs associated with late-stage interventions. The accuracy of proposed model, improve patient outcomes and reduce healthcare costs.Ultimate goal is to provide healthcare professionals with a streamlined and efficient tool for the early detection and treatment of brain tumors.

The future scope of our research encompasses several key areas. Firstly,aim to refine the CNN algorithm continually, enhancing its accuracy in detecting brain tumors. Integration with Electronic Health Records (EHRs) stands as a crucial objective to streamline healthcare workflows and improve decision-making. Expanding the web app's compatibility to include various medical imaging modalities, collaborating with medical experts for validation and refinement, and developing a mobile app version for on-the-go access are also priorities. We aspire to extend the algorithm's capabilities to detect multiple tumor types, enable real-time detection, incorporate patient data, automate tumor segmentation, and integrate with treatment planning software. These endeavours collectively represent our commitment to advancing brain tumor diagnosis and treatment.

Additionally, we will explore the realms of data augmentation and transfer learning to bolster the algorithm's adaptability, making it more versatile across various datasets and healthcare settings. The integration of interoperability standards, such as DICOM, stands as a critical objective to ensure seamless connectivity with diverse medical systems, thus expanding the web app's reach.

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