Retraction

Retraction: Brain Tumor Detection and Classification Using Deep Learning Techniques based on MRI Images (J. Phys.: Conf. Ser. 1916 012226)

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This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

IOP Publishing respectfully requests that readers consider all work within this volume potentially unreliable, as the volume has not been through a credible peer review process.

IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problematic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1

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Brain Tumor Detection and Classification Using Deep Learning Techniques based on MRI Images

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Abstract. The application of deep learning approaches in context to improve health diagnosis is providing impactful solutions. According to the World Health Organization (WHO), proper brain tumor diagnosis involves detection, brain tumor location identification, and classification of the tumor on the basis of malignancy, grade, and type. This experimental work in the diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) involves detecting the tumor, classifying the tumor in terms of grade, type, and identification of tumor location. This method has experimented in terms of utilizing one model for classifying brain MRI on different classification tasks rather than an individual model for each classification task. The Convolutional Neural Network (CNN) based multi-task classification is equipped for the classification and detection of tumors. The identification of brain tumor location is also done using a CNN-based model by segmenting the brain tumor.

Keywords: Brain tumor location identification, multi-task classification, convolutional neural network.

1. Introduction
A Brain Tumor is the uncontrolled amplification of tissue in the brain that affects brain functions [1]. The brain tumor can either be a Primary Tumor or a Secondary Tumor. This classification is based on the origin of the tumor. Brain tumors are also classified based on the malignancy of the tumor into cancerous and noncancerous tumors. They are classified on the basis of Grade as low-grade tumors - ‘Grade 1 and Grade 2’, high-grade tumors - ‘Grade 3 and Grade 4’. In addition to these categorizations, there are 120 types of brain tumors categorized by the World Health Organization (WHO) [1]. Ultrasound, Computerized Tomography (CT), Magnetic Resonance Imaging (MRI) are the major electronic modalities used. As MRI provides a three-dimensional evaluation that is in ‘pivotal, coronal and sagittal’ directions, it is mainly used for brain tumor analysis [1].

According to WHO, brain tumor detection, identifying the malignancy, the location, type, and analyzing the grade of the tumor is necessary for proper diagnosis. Identifying the brain tumor location involves the segmentation of tumors and the rest of the tasks involve classification. The dataset acquired from publicly available resources contains information about the presence, grade, location, and type of brain tumor. Equipping individual models for each of these tasks will be complex in terms of computational resources. Our main objective is to reduce this computational complexity by equipping fewer models. In this study, the classification of brain tumor tasks using Convolutional Neural Network
(CNN) based multi-task classification approach and CNN-based brain tumor segmentation for location identification.

2. Related Works

Several works have been developed to diagnose brain tumors using MRI images. The methodologies proposed in the previous studies are discussed in this section. These methods diagnose brain tumors by using techniques like classical image processing, machine learning approach based on neural networks.

A methodology that equips Threshold-based Otsu’s segmentation using Matrix Laboratory (MATLAB) which detects the tumor and segments the tumor location with an accuracy of 95% is proposed in the research work done by [1]. Classifying the brain tumor as normal and abnormal is done using the Multilayer Perceptron (MLP) which achieves an accuracy of 85% and Support Vector Machine (SVM) which achieves an accuracy of 74% in the work of [2]. An automated algorithm is designed to detect brain tumors using MRI. Feature extraction from tumor images is done using statistical feature analysis. From equations of Haralick’s features, which are dependent on the Stochastic Gradient Langevin Dynamics (SGLD) matrix of images, the brain tumor features are computed. The brain tumor detection is done using supervised learning of a feed-forward neural network with backpropagation. This achieves an accuracy of 99%. This automated algorithm to detect the tumor and present the results using a Graphic User Interface (GUI) is proposed by [3].

Precise segmentation of tumors using MRI is the most important procedure in the diagnosis of tumors. The MRI images of brain tumors are processed, converted to grayscale. Then these images are filtered using Gaussian filters, and finally, the tumor location is segmented by using the region-based segmentation method. This is implemented in MATLAB and there is appropriate information about accuracy and evaluation metrics. This work is done by S. Akbar et al and it is mentioned that there is no specific efficient strategy for segmentation of brain tumors [4]. Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and SVMs are used to detect the tumor, segment, and classify them based on malignancy. This methodology uses different wavelet levels and high accuracy is achieved using CWT. This study by M. Gurbină et al recommends using a hybrid approach for the diagnosis of brain tumors [5]. Multi-modal MRI-based automatic tumor detection algorithm involving skull extraction of T2-weighted image followed by image cutting, anomaly probabilistic map computation, feature extraction to detect the brain tumor. This methodology initially achieves an average accuracy of 90%. This methodology proposed by P. Dvorak et al shows that the accuracy of segmentation can be improved by the shape deformation feature [6].

Detecting the brain tumor area and predicting tumor type using a bounding box is proposed by R. Ezhilarasi et al. This methodology classifies the tumor as malignant, benign, glial and astrocytoma. Using Faster Region-Based Convolutional Neural Network (R-CNN) brain MRI images are trained from scratch and achieve good results [7]. CNN based brain tumor segmentation using MRI images in which High Grade Glioma (HGG) and Low Grade Glioma (LGG) parts of the tumor are found. The brain tumor type is classified using a SVM classifier which takes depth and tumor stage as parameters. This methodology is presented in work by [8]. A CNN based multi-class classification that classifies the brain tumor as aneurysms, hemorrhage, stroke, multiple sclerosis, inflammation, hydrocephalus, infectious, swelling, cysts, bleeding. This model proposed by [9] achieves 99% accuracy. A Naïve classifier is proposed by D. Divyamary et al to detect the brain tumor using MRI images and achieves an 84% accuracy [10]. Classification of brain tumor using CNN to classify the tumor as pituitary, glioma, meningioma is proposed by S. Das et al. This methodology preprocesses the brain MRI images using Gaussian filter followed by the histogram equalization technique and dropout regularization to prevent overfitting. The preprocessed images are then classified using CNN that
achieves 94.39% accuracy and average precision of 93.33%. This study claims that CNN based classification will be suitable for brain tumor diagnosis and other image-oriented diagnosis[11].

From the above studies and methodologies, most of the system has only found whether a tumor is present or not. Some have only identified the location of the tumor. Very few works have been done to classify the tumor into several categories. It is necessary to do the process in all aspects as defined by WHO to properly diagnose the tumor that is tumor detection, identifying whether it is malignant or benign, the location, type, and analyzing the grade of the tumor.

3. Proposed Method
The deep learning method used for detecting, classification, and location identification of Brain tumors is CNN based models. The CNN models are majorly used for image data, as it provides high accuracy rate. In general, a CNN is like a hierarchical model, which consists of several architectures. When a CNN model is provided with images for training, it understands the image from the base level. The two modules - Brain Tumor classification and segmentation modules in this proposed architecture are using CNN-based models. The block diagram shows the pictorial representation of the system and its modules. The architecture and workflow of the system are shown in Figure 1.

![Figure 1. The architecture of the Proposed system](image-url)
3.1. Dataset Description
The dataset is collected from Kaggle Data repositories and Cancer Imaging Archive. The data required is a multilabel dataset. To train the data for doing all the diagnosis steps, the available data to get multiple labels. We have gathered the following data:

- The brain dataset investigated in this study consists of 3064 T1-weighted contrast MR images of 233. Three different types of tumors such as meningioma, glioma, and pituitary are existing in this dataset [12].

- Rembrandt contains information produced through the Glioma Molecular Diagnostic Initiative from 874 glioma specimens comprising approximately 566,566 gene expression arrays, 834 copy number arrays, and 13,472 clinical phenotype data points [13], [14].

- Normal Brain images are acquired from Kaggle Datasets.

3.2. Data Preprocessing
Data preprocessing involves processing the raw data to obtain the data in the required format. The raw data collected from various sources in different formats such as Digital Imaging and Communications in Medicine (.dcm), Microsoft Access Table (.mat), Joint Photographic Expert Group (.jpg). The Rembrandt dataset contains the images in .dcm format and the features and labels information is provided in a comma-separated values (CSV) file. Based on the tumor location data in the features file the images containing the tumor are acquired. These images are rescaled, converted to jpg format, and stored. The Figshare data contains images in .mat format. The tumor mask data and labels are rescaled, acquired, and are converted to jpg format. The images taken from Kaggle are rescaled and stored. From the processed data and labels, the multi-label dataset is created. These images are then split into training and testing sets. The class and label information is shown in table 1.

| Classification Category | Label Information                  |
|-------------------------|-----------------------------------|
| Tumor Presence          | 1 - No Tumor                     |
|                         | 2 - Tumor Present                |
| Tumor Grade             | 1 - No Grade                     |
|                         | 2 - Grade 2                      |
|                         | 3 - Grade 3                      |
|                         | 4 - Grade 4                      |
|                         | 5 - Unknown Grade                |
| Tumor Type              | 1 - No Tumor                     |
|                         | 2 - Astrocytoma Tumor            |
|                         | 3 - Glioblastoma Multiforme (GBM) Tumor |
|                         | 4 - Mixed Tumor                  |
|                         | 5 - Oligodendroglioma Tumor      |
|                         | 6 - Meningioma Tumor             |
|                         | 7 - Glioma Tumor                 |
|                         | 8 - Pituitary Tumor              |
3.3. Brain Tumor Classification Module
The classification involves different tasks, using a different model for each task is not effective. The same brain MRI image is analyzed to classify the tumor from different perspectives. This classification can be viewed as a multi-task classification problem, which is performed with shared layers and separate layers for each task. The number of separate layers is changed as per the tasks. This module consists of a CNN-based multi-task classifier. This model is first trained with processed image data and multi-label from the data pre-processing module. The trained model is then validated with the test data set. This module gives the presence and absence of tumor and if present it also includes other labels of its grade and type. The concept of multi-task classification is inferred from the existing works of [15],[16],[17]. CNN-based multi-task classification is done using Residual Network (ResNet34). ResNet is a CNN, which is This module is shown in figure 2. This model first includes shared layers that contain ResNet34, followed by separate layers for specific tasks of brain tumor classification [15]. A set of three separate layers are chosen since this involves three classification tasks.

![Figure 2. Architecture of Multitask Classification –Brain Tumor Classification Module](image)

3.4. Brain Tumor Identification Module
Determining the location of a tumor is very important to diagnose the brain tumor. The CNN-based UNet model is equipped to segment the tumor. This model is inferred to be effective from the results in [18]. This model is first trained with image data along with the tumor mask data. The images that are detected with the tumor are processed by this UNet-CNN model to segment the tumor of the model [18]. This module gives the location of the tumor as predicted results.

4. Experimental Results
The classification module and tumor identification module were experimented with by altering the hyperparameters such as learning rate, batch, epochs. The hyperparameters that achieve better results were chosen. The trained modules are tested with the remaining twenty percent of the data. Each task-specific separate layer of the multi-task classifier equips different loss calculations, later these losses are combined. A sample result obtained is shown in figure 3. This model achieved an overall accuracy of 92%. The tumor identification module is evaluated in terms of the Dice coefficient. An average Dice score of 0.89 is obtained. The Dice coefficient for each epoch while training the UNet-CNN
module is shown in figure 4. A sample of a result obtained after the tumor identification module is shown in figure 5.

![Sample Result of Brain Tumor Classification module](image1)

**Figure 3.** Sample Result of Brain Tumor Classification module

![Brain Tumor Identification Module – Model Training DICE Score](image2)

**Figure 4.** Brain Tumor Identification Module – Model Training DICE Score

![Sample Result of Brain Tumor Identification Module](image3)

**Figure 5.** Sample Result of Brain Tumor Identification Module
5. Conclusion
Various methods have been proposed for brain tumor detection, segmentation, and classification. Most of these works are focused on major types of tumors for classification. The reason is the lack of a dataset for rarely occurring tumor types. To diagnose and treat the brain tumor, we have to find whether it is malignant or benign, its location, grade, type. A few existing methods are using different models for detection and classification, which results in more computational complexity. We have proposed the method addressing these two key issues. Our model uses the Convolutional Neural Network. In the method, all the results required to diagnose are obtained by using brain tumor classification and brain tumor identification modules. This Brain tumor classification model uses a multi-task classifier rather than using a different model for each classification. This method will be suitable even for classifying rare tumor types as the diagnosis can be done with other results obtained.

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