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تمرین،مقاله های مشابه با موضوع تشخیص تومورهای مغزی در تصاویر MRI با استفاده از تکنیک های پردازش تصویر و یادگیری ماشین

Detection of brain tumors in MRI images using image processing and machine learning techniques

۱* Early Diagnosis of Brain Tumour MRI Images Using Hybrid Techniques between Deep and Machine Learning

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Abstract

Cancer is considered one of the most aggressive and destructive diseases that shortens the average lives of patients. Misdiagnosed brain tumours lead to false medical intervention, which reduces patients' chance of survival. Accurate early medical diagnoses of brain tumour are an essential point for starting treatment plans that improve the survival of patients with brain tumours. Computer-aided diagnostic systems have provided consecutive successes for helping medical doctors make accurate diagnoses and have conducted positive strides in the field of deep and machine learning. Deep convolutional layers extract strong distinguishing features from the regions of interest compared with those extracted using traditional methods. In this study, different experiments are performed for brain tumour diagnosis by combining deep learning and traditional machine learning techniques. AlexNet and ResNet-18 are used with the support vector machine (SVM) algorithm for brain tumour classification and diagnosis. Brain tumour magnetic resonance imaging (MRI) images are enhanced using the average filter technique. Then, deep learning techniques are applied to extract robust and important deep features via deep convolutional layers. The process of combining deep and machine learning techniques starts, where features are extracted using deep learning techniques, namely, AlexNet and ResNet-18. These features are then classified using SoftMax and SVM. The MRI dataset contains 3,060 images divided into four classes, which are three tumours and one normal. All systems have achieved superior results. Specifically, the AlexNet+SVM hybrid technique exhibits the best performance, with 95.10% accuracy, 95.25% sensitivity, and 98.50% specificity.

Introduction

Cancer is one of the biggest health problems and challenges that threatens the life of humanity nowadays. After cardiovascular disorders, cancer is the second leading cause of death [1], where every sixth death is due to cancer. Among the different types of cancer, brain tumours are the most dangerous and deadly due to their heterogeneous characteristics, aggressive nature, and low survival rate. Brain tumours have numerous forms based on their shape, texture, and location, such as meningioma, glioma, acoustic neuroma, pituitary, and lymphoma [2].

The incidence of brain tumours is about 45%, 15%, and 15% for glioma, meningioma, and pituitary tumours, respectively [3]. Diagnosis is made depending on the tumour type and location, so doctors can predict patients' survival and make decisions about treatments that range from surgery to chemotherapy and radiotherapy. Therefore, a proper diagnosis of the tumour type is important in planning treatments and monitoring patients' conditions [4]. Magnetic resonance imaging (MRI) is a medical imaging technique that produces clear images of the body's internal organs without causing pain or requiring surgery, in 2D and 3D formats. It is one of the most widely used high-precision techniques for cancer detection and diagnosis [5]. However, identifying the tumour type through MRI is time-consuming, difficult, and error-prone, thereby requiring highly experienced radiologists. Due to the tumour diversity, visible features in MRI images, which enable proper decision-making, sometimes do not exist. Therefore, humans cannot easily rely on manual diagnoses. Moreover, the underdiagnosis of brain tumours is dangerous, as it reduces the response to treatments and the survival rate. Correct diagnoses help patients receive accurate treatments and survive for a long time. Accordingly, the need to use artificial intelligence (AI) techniques has become essential in diagnosing medical images, such as MRI images by the computer-aided diagnosis (CAD) system [6]. Such techniques are used to reduce workload and assist doctors and radiologists in making accurate diagnoses [7]. The CAD system comprises several stages, such as the preprocessing phase where noise is removed from images [8]; the segmentation stage where the lesion area is identified and isolated from the rest of the images [9]; the feature extraction stage where the most important features, which represent the tumour, are extracted [8]; and the classification stage where each image is classified and abnormality is predicted [10]. The literature review reveals that many machine learning algorithms have been used to classify MRI images [11–13]. Many deep learning techniques are recently used for diagnosing MRI images [14–16], which are parts of machine learning that do not require manual features. In this study, we analyse and evaluate the performance of AlexNet and ResNet-18 deep learning models for the early diagnosis of brain tumours. To evaluate the performance of deep learning (AlexNet and ResNet-18) and machine learning (support vector machine (SVM)) techniques, they are called AlexNet+SVM and ResNet-18+SVM for the early detection of brain tumours from MRI images.

The main contributions of this paper are as follows:

(i) Hybrid deep and machine learning techniques are applied where images are optimised to remove noise before they are introduced into deep learning techniques for extracting the most important deep discriminatory features; classification algorithms for convolutional neural networks (CNNs) through SoftMax and machine learning through the SVM algorithm are applied

(ii) Different structures of the CNNs of two AlexNet and ResNet-18 models and their deployment are explored to classify the MRI images of brain tumours by using a learning transfer technique

(iii) The proposed models preserve the most important local distinguishing features through the hypercolumn technique, which provides features that are inherent in the previous layer, for transfer to the next layer to increase the classification performance

(iv) The proposed models also present a promising and high-sensitivity diagnostic model for diagnosing MRI images to classify brain tumours and support the decisions of experts and radiologists

The rest of this paper is organised as follows: Section 2 reviews relevant previous studies. Section 3 provides an overview of deep and machine learning networks. Section 4 introduces the materials and methods for analysing MRI images. Section 5 presents the detailed explanations of the classification methods using CNNs and hybrid methods. Section 6 provides the experiment results. Section 7 discusses and compares the results with relevant studies. Section 8 concludes the paper.

Conclusion

The detection of a brain tumour is a major challenge due to the complex brain structure. The brain is responsible for controlling the functions of all the body organs. The automatic classification of early-stage brain tumours using deep and machine learning techniques plays an important role. These systems allow for timely diagnosis and increase patients' chance of survival. These techniques also help experts and radiologists in making decisions regarding diagnosis and treatment plans. We conducted four experiments to diagnose three types of MRI images of brain tumours (meningioma, glioma, and pituitary) and one class that contains healthy images. We used a new approach where we hybrid deep learning models with machine learning techniques (i.e., AlexNet, AlexNet+SVM, ResNet-18, and ResNet-18+SVM). Images were improved with the average and Laplacian filters. The enhanced images were introduced into deep learning models to extract deep and discriminatory features. Deep features were diagnosed using CNN classifiers, which are SoftMax, and machine learning classifiers called SVM algorithms. All the proposed systems yielded promising results for diagnosing MRI images of brain tumours, with little difference in accuracy among models. There are significant differences in the computational cost during training the dataset. The training of the dataset by the AlexNet model consumed 47 min 35 sec. In contrast, the computational cost of training the dataset by the ResNet-18 model was 349 min 13 sec. It is noted that the computational cost is high. In contrast, when applying the hybrid techniques between CNN models and the SVM algorithm, the computational cost was low as follows. The dataset was trained by the AlexNet+SVM hybrid model through 3 min 21 sec, while the computational cost of training the dataset by the ResNet-18+SVM hybrid model was 2 min 23 sec. A laptop Intel ® i5 laptop 6 generations, 12 GB RAM, and 4 GB GPU GEFORCE, is used to run the experiments. The AlexNet+SVM hybrid model exhibited the best performance among others. Specifically, it achieved 95.1%, 95.25%, and 98.50% accuracy, sensitivity, and specificity, respectively.

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۲* Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques

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Abstract

Radiology is a broad subject that needs more knowledge and understanding of medical science to identify tumors accurately. The need for a tumor detection program, thus, overcomes the lack of qualified radiologists. Using magnetic resonance imaging, biomedical image processing makes it easier to detect and locate brain tumors. In this study, a segmentation and detection method for brain tumors was developed using images from the MRI sequence as an input image to identify the tumor area. This process is difficult due to the wide variety of tumor tissues in the presence of different patients, and, in most cases, the similarity within normal tissues makes the task difficult. The main goal is to classify the brain in the presence of a brain tumor or a healthy brain. The proposed system has been researched based on Berkeley's wavelet transformation (BWT) and deep learning classifier to improve performance and simplify the process of medical image segmentation. Significant features are extracted from each segmented tissue using the gray-level-co-occurrence matrix (GLCM) method, followed by a feature optimization using a genetic algorithm. The innovative final result of the approach implemented was assessed based on accuracy, sensitivity,

specificity, coefficient of dice, Jaccard's coefficient, spatial overlap, AVME, and FoM.

Introduction

Every year, more than 190,000 people in the world are diagnosed with primary or metastatic brain (secondary) tumors. Although the causes of brain tumors are not certain, there are many trends among the people who get them. Any human being, whether a child or an adult, may be affected by it. The tumor region has initially identified a reduction in the risk of mortality [1]. As a result, the radiology department has gained prominence in the study of brain tumors using imaging methods. Many studies have looked at the causes of brain tumors, but the results have not been conclusive. In [2], an effective partitioning strategy was presented using the *k*-means clustering method integrated with the FCM technique. This approach will benefit from the *k*-means clustering in terms of the minimum time of calculation FCM helps to increase accuracy. Amato et al. [3] structured PC-assisted recognition using mathematical morphological reconstruction (MMR) for the initial analysis of brain tumors. Test results show the high accuracy of the segmented images while significantly reducing the time of calculation. In [4], classification of neural deep learning systems was proposed for the identification of brain tumors. Discrete wavelet transformation (DWT), excellent extraction method, and main component analysis (PCA) were applied to the classifier here, and performance evaluation was highly acceptable across all performance measurements.

In [5], a new classifier system was developed for brain tumor detection. The proposed system achieved 92.31% of accuracy. In [6], a method was suggested for classifying the brain MRI images using an advanced machine learning approach and brain structure analytics. To identify the separated brain regions, this technique provides greater accuracy and to find the ROI of the affected area. Researchers in [7] proposed a strategy to recognize MR brain tumors using a hybrid approach incorporating DWT transform for feature extraction, a genetic algorithm to reduce the number of features, and to support the classification of brain tumors by vector machine (SVM) [8]. The results of this study show that the hybrid strategy offers better output in a similar sense and that the RMS error is state-of-the-art. Specific segmentation concepts [9–33] include region-based segmentation [10], edge-based technique [11], and thresholding technique [12] for the detection of cancer cells from normal cells. Common classification method is based on the Neural Network Classifier [13], SVM Classifier [14], and Decision Classifier [15]. In [32], a brain tumor detection method was developed using the GMDSWS-MEC model. The result shows high accuracy and less time to detect tumors.

1.1. Research Gap Identified

From the research analysis, we have identified that traditional algorithms are very effective to the initial cluster size and cluster centers. If these clusters vary with different initial inputs, then it creates problems in classifying pixels. In the existing popular fuzzy cluster mean algorithm, the cluster centroid value is taken randomly. This will increase the time to get the desired solution. Manual segmentation and evaluation of MRI brain images carried out by radiologists are tedious; the segmentation is done by using machine learning techniques whose accuracy and computation speed are less. Many neural network algorithms have been used for the classification and detection of the tumor where the accuracy is less. The detection accuracy is based on the segmentation and the detection algorithms used. So far, in an existing system, the accuracy and the quality of the image are less.

1.2. Contribution of the Proposed Research

The proposed technique is an effective technique to detect tumour from MRI images. In the proposed technique, different classifiers are used. The proposed system should be capable of processing MRI, multislice sequences, accurately bounding the tumor area from the preprocessed image via skull stripping and morphological operations. The region should be segmented by Berkeley's wavelet transformation and extract the texture features using ABCD, FOS, and GLCM features. Classifiers such as Naïve Bayes, SVM-based BoVW, and CNN algorithm should compare the classified result and must identify the tumor region with high precision and accuracy. Finally, based on the classifier result, the tumor region is classified into malignant or benign.

The rest of the article is intended to continue: section 1 presents the background to brain tumors and related work; section 2 presents the construction techniques with the measures used throughout the method used; section 3 describes the results and analysis and the comparative study; and, finally, section 4 presents the conclusions and upcoming work.

Conclusion

Medical image segmentation is a challenging issue due to the complexity of the images, as well as the lack of anatomical models that fully capture the potential deformations in each structure. This proposed method works very effectively to the initial cluster size and cluster centers. The segmentation is done by using BWT techniques whose accuracy and computation speed are less. This work recommends a system that requires negligible human intrusion to partition the brain tissue. The main aim of this recommended system is to aid the human experts or neurosurgeons in identifying the patients with minimal time. The experimental results show 98.5% accuracy compared to the state-of-the-art technologies. Computational time, system complexity, and memory space requirements taken for executing the algorithms could be further reduced. The same approach can be also used to detect and analyze different pathologies found in other parts of the body (kidney, liver, lungs, etc.). Different classifiers with optimization methodology can be used in future research to improve accuracy by integrating more effective segmentation and extraction techniques with real-time images and clinical cases using a wider data set covering various scenarios.

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3* A Novel Deep Learning Method for Recognition and Classification of Brain Tumors from MRI Images

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Abstract:

A brain tumor is an abnormal growth in brain cells that causes damage to various blood vessels and nerves in the human body. An earlier and accurate diagnosis of the brain tumor is of foremost important to avoid future complications. Precise segmentation of brain tumors provides a basis for surgical planning and treatment to doctors. Manual detection using MRI images is computationally complex in cases where the survival of the patient is dependent on timely treatment,and the performance relies on domain expertise. Therefore, computerized detection of tumors is stilla challenging task due to significant variations in their location and structure, i.e., irregular shapesand ambiguous boundaries. In this study, we propose a custom Mask Region-based Convolution neural network (Mask RCNN) with a densenet-41 backbone architecture that is trained via transferlearning for precise classification and segmentation of brain tumors. Our method is evaluated on two different benchmark datasets using various quantitative measures. Comparative results showthat the custom Mask-RCNN can more precisely detect tumor locations using bounding boxesand return segmentation masks to provide exact tumor regions. Our proposed model achievedan accuracy of 96.3% and 98.34% for segmentation and classification respectively, demonstrating enhanced robustness compared to state-of-the-art approaches.

Introduction

A brain tumor is a fatal disease-causing death to thousands of people around the globe. A brain tumor is mainly caused by abnormal growth in brain tissues. As the skull portion of the human body is inflexible and small, any growth inside the brain may affect the functionality of the human organ depending on its origin and position. Moreover, it may also spread in other parts of the body and affect their functionality [1]. Usually, the brain tumor is categorized into two classes, named primary and secondary based on its position. The primary tumor comprises 70% of all brain tumors while the remaining 30% are secondary [2]. A primary brain tumor includes tumors that originate from the brain cells while a secondary brain tumor first originates in another organ and then transfers to the brain through the circulation of the blood [3]. According to an NBTF study, in the USA an estimated 29,000 cases are diagnosed with primary brain tumor, among which, around 13,000 patients die per year [4]. Similarly, in the UK, more than 42,000 patients with a primary brain tumor die annually. Among various primary brain tumor types, glioma has the highest mortality and mobility rate [5]. Gliomas usually grow from glial cells of the brain [1] and are classified as low-grade (LG) glioma and high-grade (HG) glioma. The HG glioma is more lifethreatening and intense and usually, the victim can survive for two years [6]. A meningioma tumor usually develops in the protective membrane layer which acts as a covering of the human brain and spinal cord. Mostly, meningioma tumors are less threatening and slowgrowing [7]. The pituitary tumor starts developing in the pituitary gland, which is located at the base of the brain and is involved in the production of several essential hormones in the body [8]. A pituitary tumor is a benign tumor; however, serious complications may cause hormonal deficiencies or permanent loss of vision because of the overproduction of hormones [1]. Hence, an early-stage detection of brain tumors is critical and is of extreme clinical interest. If it is not diagnosed on time, the disease could become life-threatening or may result in the disability of a person [7]. Depending on the situation and their purpose, numerous medical imaging techniques can be used in clinical practices for tumor diagnosis [9]. Some of those techniques are ultrasonography (US), magnetic resonance imaging (MRI), and computed tomography (CT) [10]. The MRI is the most common non-invasive imaging technique because it uses no damaging ionizing radiations of X-rays during the scan. Moreover, it provides high-quality images of soft tissue without any risk, plus an ability to acquire multiple modalities, e.g., T1, T1c, T2, and FLAIR, using various parameters. Each of these modalities produces noticeably a unique tissue contrast [11]. For timely treatment, the top priority of a neurosurgeon is to mark out tumor regions as precisely as possible, otherwise excessive or insufficient cutting may lead to suffering or a permanent loss. Unfortunately, this manual segmentation process is laborious and time-consuming and yields poor segmentation results [12]. Hence, the use of computeraided brain tumor segmentation algorithms using MRI to identify and segment brain tumors has received considerable attention from the research community. Therefore, there is a significant need for automated and efficient tumor detection and segmentation technique. Despite recent developments in automatic or semi-automatic techniques for tumor segmentation, it is still a challenging task to segment a tumor accurately because of the following reasons [13]. First, there is a significant change in tumor location, shape, appearance, and size from patient to patient [14]. Second, the tumor boundaries can be discontinuous or blurry as the tumor regions are usually occupied by surrounding healthy tissues [15]. Third, the addition of inadequate signal-to-noise ratio or image distortion usually caused by different factors such as MRI acquisition protocols or variation in imaging devices may further increase the difficulty and influence the precision of final segmentation [16]. The brain tumor detection approaches can be divided into two types, named machine learning (ML)-based [17] and deep learning (DL)-based [18] methods. ML-based techniques mainly include support vector machine [19], conditional random forest [20], decision tree [21], principal component analysis [22], and fuzzy c-means [23]. These techniques require hand-crafted features. The hand-crafted features, here, mean that the features are required to be extracted from training images to start the learning process and perhaps require an expert with extensive knowledge to identify the most important features. Hence, the detection accuracy of the ML-based techniques is dependent on the quality and representation of the extracted features, thus is limited and prone to errors in dealing with large datasets [24]. Meanwhile, DL-based algorithms have shown high performance in various industries including medical imaging [25–27]. The most common or well-known DL model is the convolutional neural network (CNN) that can instinctively learn dense characteristics directly from the training data due to its weight-sharing nature [28]. Based on these advantages, DL-based brain tumor segmentation has grabbed the researcher's attention [29]. Relevant works include patch-based CNN [30], patch-based multi-scale CNN [31], patch-based DCNN [32], fully convolution-based CNN (FCNN) [33], and U-net based [34] brain tumor segmentation models. The patch-based approaches take a small portion of the image as input to CNN and classify each patch into a different class, which degrades the image content and label correlation. The FCNN, on the other hand, is a modified form of CNN, which predicts probability distribution pixel-wise instead of making patch-wise probability distribution predictions [35]. This improvement enables FCNN to take the full-sized image and perform the prediction for the whole image in just a single forward pass. Despite recent advances, the existing DL-based techniques require several convolution layers (CLs) and kernels, increasing the computational cost resultantly. Hence, an efficient method for accurate tumor identification and segmentation with a less complex network in terms of memory and computing resources usage is still in demand [36]. In this paper, we proposed an automated approach for brain tumor detection and segmentation using MRI images. The proposed technique adopts a DL model using a fully convolution neural network, Mask-RCNN [37] with DenseNet-41 backbone, and utilizes a multitask loss function to achieve an end-to-end training of deep CNN, increasing the detection accuracy. The motivation behind using a custom Mask-RCNN was to achieve a similar level of accuracy with a comparatively simple model, fewer kernels, and two convolutional layers. To show the efficiency of the proposed approach, we evaluated our model on free and online available brain tumor datasets [38,39] using various quantitative measures. The results of brain tumor MRI segmentation are validated through ground truth analysis. The recent works have investigated the effectiveness of a Mask-RCNN model on 3D images of the brain [40] and in other medical fields such as oral disease [41],breast tumor [42], and lung tumor [43] detection and segmentation. The main contributions of the proposed work are as follows:1. The proposed method can precisely segment and classify the brain tumors from MRI images under the presence of blurring, noise, and bias field-effect variations in input images.

2. We have created the annotations which are essential for the training of the proposed model because available datasets do not have a bounding box and mask groundtruths (GTs).

3. The accurate localization and segmentation of tumor regions due to an effective region proposal network of DenseNet-41-based Mask-RCNN as it works in an end-toend manner. 4. Extensive experiments are performed using two different datasets to show the robustness of the presented framework and compared obtained results with the existing state-of-the-art methods.The rest of our paper develops the following structure: the literature review is explained in Section 2, while the brief description of the proposed work is defined in Section 3.In Section 4, the datasets, evaluation parameters used, and experimental results obtained are reported. Finally, a conclusion of this work is described in Section 5.

Conclusions

In this work, we introduced a DL technique, namely Mask-RCNN with two backbones,ResNet-50 and DenseNet-41, for precise and automated segmentation of brain tumor regions from MRI images. We obtained better segmentation and classification results for DenseNet-41 based

Mask-RCNN as compared to the ResNet-50 network, due to its dense connections which result in more robust image feature calculations. Comparative experimental results show that our proposed method more precisely delineates the tumor region and can serve as a new automated tool for diagnostic purposes. Moreover, as compared to state-of-the-art models, our Custom Mask-RCNN can compute deep features with effective representations of brain tumors. In future, we aim to perform classification along with segmentation of brain tumors using more challenging datasets. We also plan to evaluate the robustness of our Custom Mask-RCNN for other medical image analyses applications such as eye disease detection, finger skin recognition, skin cancer, and COVID detection. Furthermore, we aim to increase training samples and optimize hyper-parameters to further improve the accuracy of the model. Author Contributions: Conceptualization, M.M., T.N., M.N.,and A.M.; data curation, M.M., T.N., M.N. and A.M.; formal analysis, J.R., T.M.,H.-Y.K., A.H.; funding acquisition, H.-Y.K.; investigation,J.R., H.-Y.K. and A.H.; methodology, T.N., J.R. and M.N.; project administration, T.N., J.R.; resources,A.M.; software, A.M. and M.M.; supervision, J.R.; validation, T.N.; visualization, J.R.; writing—original draft, M.M., T.N., M.N., J.R.; writing—review and editing, M.M., T.N., M.N., A.M., J.R.,H.-Y.K., T.M. and A.H. All authors have read and agreed to the published version of the manuscript.Funding: This study was supported by the Research Program funded by the SeoulTech (Seoul National University of Science and Technology). Institutional Review Board Statement: Not applicable. Informed Consent Statement: Not applicable. Data Availability Statement: Data sharing not applicable to this article as authors have used publicly available datasets, whose details are included in the "experimental results and discussions" section of this article. Please contact the authors for further requests. Conflicts of Interest: The authors declare no conflict of interest.

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۴* A framework for brain tumor detection based on segmentation and features fusion using MRI images

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Abstract

Irregular growth of cells in the skull is recognized as a brain tumor that can have two types such as benign and malignant. There exist various methods which are used by oncologists to assess the existence of brain tumors such as blood tests or visual assessments. Moreover, the noninvasive magnetic resonance imaging (MRI) technique without ionizing radiation has been commonly utilized for diagnosis. However, the segmentation in 3-dimensional MRI is time-consuming and the outcomes mainly depend on the operator's experience. Therefore, a novel and robust automated brain tumor detector has been suggested based on segmentation and fusion of features. To improve the localization results, we pre-processed the images using Gaussian Filter (GF), and SynthStrip: a tool for brain skull stripping. We utilized two known benchmarks for training and testing i.e., Figshare and Harvard. The proposed methodology attained 99.8% accuracy, 99.3% recall, 99.4% precision, 99.5% F1 score, and 0.989 AUC. We performed the comparative analysis of our approach with prevailing DL, classical, and segmentation-based approaches. Additionally, we also performed the cross-validation using Harvard dataset attaining 99.3% identification accuracy. The outcomes exhibit that our approach offers significant outcomes than existing methods and outperforms them.

Introduction

The irregular progression of cells in the brain skull is identified as brain tumor. The brain serves as a command center for the human body; therefore, skull tumors may severely affect human health (Díaz-Pernas et al. 2021). According to the report, brain tumors are responsible for 85–90 % of the whole central nervous system's tumors (Amanullah et al. 2022). Radiologists have employed numerous imaging techniques, namely MRI and CT scans, to detect tumors in the brain. Moreover, MRIs present imaging with higher resolution than CT scans. Due to the astronomical nature of MRI, it is widely used to detect malignant brain tumors (Chatterjee 2021). Then, after imaging, radiologists analyze those images manually and identify the location. Moreover, the grading of tumors is a time taking process that demands high expertise from radiologists. The results may be inaccurate and require high cost. The challenges in identifying tumors include irregular shapes and various types exhibiting similar appearance and dimensions. The erroneous diagnosis may cause severe complications for the patient's health and reduces survival chance. To address the challenges mentioned above, the room for developing a computerized brain tumor recognition system is gaining significant popularity(Anitha and Murugavalli 2016). Numerous researchers have developed a computerized system based on traditional machine learning approaches employing processes such as pre-processing, manual feature extraction, dimensionality reduction, and catagorization (El-Dahshan et al., 2014, Mahum et al., 2021, Mahum et al., 2022).The crucial step is feature extraction to develop an accurate automated brain tumor detector. Thus, the ML-based method's performance relies on feature types and nature. The classical machine learning techniques may fail to detect the tiny tumors in unseen test samples during the training phase. Furthermore, they become slow when we deal with large datasets of brain MRIs. The ML-based approaches include Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Trees. Additionally, some segmentation-based techniques also have been proposed by the researchers. The tumor is segmented as a region of interest (ROI) using segmentation algorithms, and then features are extracted from ROI. The steps for segmentation-based approaches for brain tumor detection include pre-processing, ROI extraction, feature extraction, training, and classification. However, the existing techniques still lack accuracy due to the brain's complex structure. Therefore, an effective and efficient model is required for the timely detection of brain tumors requiring minimum human effort.

The advantage of Convolutional Neural Network (CNN) over ML techniques is that it performs automatic feature extraction (Munir et al., 2022). Some famous DL models are GoogleNet, ResNet, InceptionNet, VGGNet, AlexNet, and DenseNet (Nazir et al., 2021). Simple classification techniques for brain tumor detection do not provide information on the location for the tumor, therefore, giving rise to a false positive rate. Various object detection approaches have been utilized for brain tumor recognition to overcome the mentioned drawback. The deep learning-based method has been proposed by researchers (Masood et al.,

2022) using CenterNet for the localization of brain tumors. They utilized ResNet34 with an attention block as the base network of CenterNet. Although, the object detection-based methods exist for brain tumor detection, they use extensive hyper-parameters and require a high computational cost.

Despite recent developments in segmentation-based methods for brain tumor detection, there exist numerous challenges due to variations in size, regularity, location, shape, and texture (Dong et al., 2017). On the other side, classical methods are less generalized due to small dataset size for training. Moreover, classical techniques may fail on unseen data. Therefore, to overcome the challenges of existing techniques, in this work, we suggest a novel brain tumor detection for early diagnosis based on feature fusion using classical and DL method. Our proposed method effectively extracts the keyfeatures and provides a hybrd feature vector from the tumorous part. More specifically, we pre-process the brain images in the first phase to enhance the contrast using gausian filtering. In the second phase, we employ segmentation for the localization of the tumor. In the third phase, we extracted features from the segmented image using a deep convolutional neural network, i.e., DarkNet19 and local binary patterns. In the final step, we fused the extracted features and trained the BiLSTM network for the multi-classification, such as the pituitary, glioma, and meningioma. Our proposed system effectively identifies the locations of the tumors and improves the detection accuracy based on extracted key features from the segmented region.

The offerings of our work are below:

To suggest a novel model based on segmentation and features fusion that can effectively localize and classifies the tumors in MRI images.

To develop a technique that is able to localize tiny tumors in MRI scans and is better in the early detection of brain tumors.

To suggest a robust system that can precisely locate and detect the tumors in unseen MRI scans.

An extensive experimentations has been executed to assess the efficacy of the suggested system in terms of accuracy and robustness. The results ensure the significant performance of the suggested model for early brain tumor recognition and categorization.

The remaining work is described as: section 2 discussed existing methods, section 3 demonstrated the proposed technique, section 4 and 4 explains the experimental assessment and conclusion respectively.

Conclusions

In this work, a robust brain tumor detection method has been suggested based on fusion of features. Our suggested method pre-process the samples using Gaussian filtering in first step to reduce the noise from the brain samples. To improve the localization results on MRIs, we used an open source tool i.e, SynthStrip for the stripping of brain skull. Then, the segmentation algorithm was employed for the localization of tumors in the brain MRI images. After this, features were gathered using HOG

CRediT authorship contribution statement

Almetwally Mohamad Mostafa: Methodology, Software, Writing – review & editing. Mohammed A. El-Meligy: Data curation, Writing – original draft. Maram Abdullah Alkhayyal: Conceptualization, Writing – review & editing, Validation. Abeer Alnuaim: Writing – review & editing. Mohamed Sharaf: Visualization, Investigation, Writing – review & editing, Supervision, Software, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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۵ *Automatic detection of brain tumors with the aid of ensemble deep learning architectures and class activation map indicators by employing magnetic resonance images

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Abstract

Today, as in every life-threatening disease, early diagnosis of brain tumors plays a life-saving role. The brain tumor is formed by the transformation of brain cells from their normal structures into abnormal cell structures. These formed abnormal cells begin to form in masses in the brain regions. Nowadays, many different techniques are employed to detect these tumor masses, and the most common of these techniques is Magnetic Resonance Imaging (MRI). In this study, it is aimed to automatically detect brain tumors with the help of ensemble deep learning architectures (ResNet50, VGG19, InceptionV3 and MobileNet) and Class Activation Maps (CAMs) indicators by employing MRI images. The proposed system was implemented in three stages. In the first stage, it was determined whether there was a tumor in the MR images (Binary Approach). In the second stage, different tumor types (Normal, Glioma Tumor, Meningioma Tumor, Pituitary Tumor) were detected from MR images (Multi-class Approach). In the last stage, CAMs of each tumor group were created as an alternative tool to facilitate the work of specialists in tumor detection. The results showed that the overall accuracy of the binary approach was calculated as 100% on the ResNet50, InceptionV3 and MobileNet architectures, and 99.71% on the VGG19 architecture. Moreover, the accuracy values of 96.45% with ResNet50, 93.40% with VGG19, 85.03% with InceptionV3 and

89.34% with MobileNet architectures were obtained in the multi-class approach.

Introduction

The brain, one of the most complex organs in the human body, consists of billions of cells. Brain tumor occurs when these cells divide in or around the brain in an uncontrolled way. This group of cells that divide uncontrollably can affect the function of other healthy cells and the brain. These tumors that arise in the brain or appear elsewhere in the body and moved to the brain; can be classified as benign-malignant, low-high grade and glioma meningioma-pituitary etc. depending on several factors such as location, shape and texture [1], [2], [3], [4]. Early diagnosis of the tumor and automatic classification of tumor type are vital for physicians in planning tumor treatments [5].

Various imaging methods such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) are employed to identify brain tumors. Among these methods, MRI is widely utilized since it performs this procedure in 2D and 3D dimensional formats, with excellent image quality, painlessly and without radiation [6]. Furthermore, MRI is considered to be the most accurate and widely used technique in the detection and classification of brain tumors because it provides high resolution images on brain tissue [7]. However, simultaneous manual analysis of large numbers of MR images for disease detection by specialists requires both a heavy workload and a waste of time. In order to prevent this situation, Artificial Intelligence (AI) technologies have been of great importance recently.

In parallel with the developments in the field of AI technologies; Computer Aided Diagnosis (CAD) systems, in which fast and effective treatment methods such as diagnosis and classification of cancer and brain tumors are developed and designed, are widely employed nowadays. A typical CAD system generally consists of three phases; the first is to separate the lesions from the images, the second is to extract the characteristics of these separated tumors by analyzing them with mathematical parameters, and finally, to utilize an appropriate Machine Learning (ML) approach in order to predict abnormality classification [8].

ML based smart system applications have been employed in many areas recently. The quality of these systems depends on finding or extracting good features. Deep Learning (DL) is an advanced subset of machine learning algorithms and it is a structure designed in a structure where various nonlinear layers and each successive layer use the output of the previous layer as input to extract features better [9]. Among DL techniques, Convolutional Neural Networks (CNN) is a part of the deep learning family and a type of multi-layer perceptron (MLP). CNN algorithms have been employed in many different fields in medicine, especially in the field of image processing and they represent the latest technology in machine learning used in the field of disease diagnosis based on MRI images [10], [11], [12]. The CNN is widely employed for classification and grading of medical images since it does not require processes such as pre-processing and feature extraction prior to the training process.

Considering the literature studies, ML and DL based approaches for brain tumor identification can be divided into two main groups: first, dividing the MR images into two main categories as normal and abnormal, and then detecting the abnormal brain MR images according to various types of brain tumors [13], [14]. In this context, recent works in the literature are given respectively. Rehman et al. proposed three different CNN deep learning architectures (GoogleNet, AlexNet and VGGNet) in order to classify different types of tumors (pituitary gland tumors, glioma tumors and meningioma tumors) by employing brain MRI data sets. As a result, they achieved 98.69% accuracy using the

VGG16 architecture [15]. Afshar et al. suggested a Capsule Network (CapsNet) to classify brain tumors. Moreover, they obtained CapsNet feature maps from different convolution layers to improve accuracy performance. Finally, they calculated the classification performance as 86.50% [16]. Khawaldeh et al. recommended a system for grading glioma brain tumors by employing AlexNet, which is a different version of the CNN. As a result, they achieved a reasonable performance with an accuracy of 91.16% via utilizing image-level whole brain MR images [17]. Abiwinanda et al. proffered a deep CNN-based system for brain tumor detection and grading. The proposed system is based on Fuzzy C-Means (FCM) for brain segmentation. Finally, the results showed that the application achieved an accuracy rate of 97.5% [18]. Anaraki et al. suggested a system that combines Discrete Wavelet Transform (DWT) features and DL techniques. Moreover, they employed the fuzzy k-mean method to segment the brain tumor and Principal Component Analysis (PCA) to reduce the size of the features. Finally, they reached accuracy of 96.97% [19]. Widhiarso et al. proposed a brain tumor classification system employing the CNN architecture and Gray Level Co-Formation Matrix (GLCM). They extracted four features (Energy, Correlation, Contrast, and Homogeneity) from four angles (0°, 45°, 90° and 135°) for each image. Finally, a success of 82.27% was achieved in the study [20]. Cheng et al. recommended an approach to improve the performance of the brain tumor classification system thanks to tumor region augmentation and partition. In their study, they implemented three feature extraction methods (intensity histogram, GLCM and Bag of Words) to form feature vectors and these features were then employed in a classifier. As a result, they achieved a classification performance between 71.39% and 91.28% [21]. Sajjad et al. proffered VGG-19 DL technique for the classification of four different tumor types and segmented the tumor regions with the help of deep features. For training, they used eight different data augmentation techniques with a total of 30 parameters by expanding the existing data sets. Finally, the proposed study performed convincing results compared to existing methods [22]. Alanazi et al. recommended early diagnoses of brain tumor employing CNN and MRI images. Finally they observed a high accuracy between 95% and 96% [23]. Khan et al. proposed an intelligent system for detecting and classifying brain tumors by using CNN and MRI images. Their result showed that an accuracy 92.13% was observed [24]. Wahlang et al. suggested LeNet, AlexNet, ResNet architectures for brain tumor detection from MRI images. Their result achieves 92.13% precision [25]. Neelima et al. recommended an automatic mechanism that can perform the cataloguing of tumor with MRI. In the study, 91.7% accuracy was observed with CNN and CAViaRSPO-based GAN method [26].

In this study, it is aimed to automatically detect brain tumors with the help of ensemble DL architectures (ResNet50, VGG19, InceptionV3 and MobileNet) and CAMs indicators by employing MRI images. For this purpose, the study was carried out in three steps. In the first step, it is determined whether there is a tumor in the MR images with binary approach. In the second step, different tumor types (Normal, Glioma Tumor, Meningioma Tumor, Pituitary Tumor) are detected from MRI images with multi-class approach. In the last step, CAMs of each tumor group are created as an alternative tool in tumor detection.

The major contributions of this study can be listed as follows:

1.The ensemble DL based pipeline is proposed for low-cost and effective detection of brain tumors.

2.Different deep learning architectures (ResNet50, VGG19, InceptionV3 and MobileNet) have been processed with the ensemble approach, and the optimum recognition system has been determined by choosing the most appropriate DL architecture parameters.

3.Additionally, CAMs belonging to each tumor group have been created as an alternative tool in order to save time and to facilitate the work of specialists in tumor detection.

The rest of this work is organized as follows. In Section-2, the dataset and the ensemble DL architectures employed in this study are explained. In the Section-3, the results obtained from different DL architectures are presented and the obtained results are evaluated. Finally, in the Section-4, the proposed study is summed up.

Conclusion

This study was carried out in three stages. In the first step, tumor detection was made from MRI images with a binary approach. In the second stage, images of four classes (normal, Glioma tumor, Meningioma tumor and Pituitary tumor) were classified with a multi-classification approach. In the third step, CAMs of each tumor group were created as an alternative tool to facilitate the work of specialists in tumor detection. Moreover, accuracies and time performances of the proposed system were obtained by employing ResNet50, VGG19, InceptionV3 and MobileNet deep learning architectures. In general, VGG19 architecture showed the lowest and slowest performance in brain tumor detection from MRI images with binary approach while VGG19 architecture performed better than InceptionV3 and MobileNet DL architectures for multi- classification. We hope that the results of this study will give insight to researchers who will utilize deep learning architectures for classification, detection, recognition and time performance in the future.

Declaration of Competing Interest

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۶* An intelligent driven deep residual learning framework for brain tumor classification using MRI images

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Abstract

Brain tumor classification is an expensive complicated challenge in the sector of clinical image analysis. Machine learning algorithms enabled radiologists to accurately diagnose tumors without requiring major surgery. However, several challenges rise; first, the major challenge in designing the most accurate deep learning architecture for classifying brain tumors; and secondly, difficulty of finding an expert who is experienced in the field of classifying brain tumors using images by deep learning models. These difficulties made us motivated to propose an advanced and high accurate framework based on the concepts of deep learning and evolutionary algorithms to automatically design the ResNet architecture efficiently for classifying three types of brain tumors on a large database of MRI images. Thus, we propose an optimization-based deep convolutional ResNet model combined with a novel evolutionary algorithm to optimize the architecture and hyperparameters of deep ResNet model automatically without need of human experts as well manual architecture design which is complicated task to classify different types of brain tumor. Also, we propose an improved version of ant colony optimization (IACO) based on the concepts of differential evolution strategy and multi-population operators. These two concepts make an effective balance for solution diversity and convergence speed as well as enhancing the optimization performance and avoiding falling into the local optima for designing the deep learning-based ResNet architectures. The experimental finding revealed that our proposed framework obtained an average accuracy of 0.98694 which efficiently

shows that our IACO-ResNet algorithm can help excellently with the automatic classification of brain tumors.

Introduction

The human brain is an essential decision-making part of the body surrounded by a rigid skull. A brain tumor is a group of irregular cells in the brain that forms a mass. Any expansion in such an area will cause serious problems. Brain tumors include the most threatening types of tumors worldwide (Van Meir et al., 2010). Glioma is the most common primary brain tumor caused by carcinogenesis of glial cells in the spinal cord and brain. Intracranial pressure increases with the development of benign or malignant tumors. The tumor leads to permanent brain damage and even death. Approximately 86,000 new cases of brain tumors were diagnosed in 2019. Since 2019, approximately 17,000 people have died from this disease (Rehman et al., 2021). In this way, scientists and researchers have developed sophisticated techniques and methods for identifying brain tumors. Magnetic resonance imaging (MRI) and computed tomography (CT) are two methods that are widely used to mark abnormalities in the shape, size, or location of brain tissue. Of the two methods, MRI is the most preferred by physicians and researchers are increasingly focused on. The MRI of three types of tumors is shown in Fig. 6.

Automated approaches, implemented mainly by computer-aided medical imaging techniques, are increasingly helping physicians classification brain tumors. Machine learning (ML) algorithms gain insight from training data samples and predict the class label of unknown data objects. ML algorithms are commonly used in the field of health informatics (Ravì et al., 2016), pandemic prediction (Ahmadian, Jalali, Islam et al., 2021, Jalali, Ahmadian, Ahmadian et al., 2021), and modeling the complex plant (Mehnatkesh et al., 2020). ML has advanced greatly in the medical field. For example, in Goel, Murugan, Mirjalili, and Chakrabartty (2020), they have used optimally structured convolutional networks to automatically diagnose COVID-19. Also, many ML-based studies have been performed on MR images to classify brain tumors (Kaur et al., 2020, Pandiselvi and Maheswaran, 2019, Tiwari et al., 2020). Medical image processing consists of two general parts. The first part deals with enhancement, feature selection, filter application, and segmentation which is known as pre-processing and the second part deals with identification and/or classification, which is called post-processing (Bankman, 2008). Conventional machine learning and a deep learning approach can be implemented to achieve these demands. With the help of a conventional machine learning approach and manual extraction of features, the required results can be extracted from the images very quickly. Unlike conventional machine learning in the deep learning approach to extract the results from images, the feature is not extracted manually. It only needs to design the model that includes proper selection of the number of layers, activation function, integration, and sometimes pre-trained models. Although a conventional machine learning approach is faster than a deep learning approach, a deep learning approach is better accurate and more robust than a conventional machine learning approach. Several papers have been conducted focusing on diagnosing brain tumors using MRI images through machine learning approaches.

In Ismael, Mohammed, and Hefny (2020), a deep learning model for brain tumor classification from MRI images is proposed and the proposed model is evaluated under several performance criteria. This paper used the Residual Network architecture in order to improve its performance. In Khan et al. (2020) the brain tumor images were fed to Convolutional Neural Network (CNN) for feature extraction. After feature extraction, the Minimum Redundancy Maximum Relevance (mRMR) algorithm is used to select the most efficient deep features. Finally, the deep features selected in the classification module are fed into the SVM. In this article, the Black Widow Optimization Algorithm

(BWOA) was used to optimally adjust the parameters of CNN and SVM. One of the methods for diagnosing the type of cancer is clustering methods. In Diallo et al. (2021), a Deep Embedding Clustering algorithm based on Contractive Autoencoder (DECCA) to automatically cluster documents was recommended. They have effectively solved the existing optimization with small stochastic gradient descent and deterministic backpropagation, and with the help of appropriate loss function, they have avoided uninterested clusters. In Khan, Hu, Li, Diallo, and Zhao (2022), a new low-rank sparse display method based on three-way clustering was designed. Finally, a new objective function is constructed to maintain consistency between views using the low-rank sparse representation technique, and the entire objective function is optimized using the augmented Lagrange coefficient algorithm. Several models that attempt to find accurate and efficient boundary curves of brain tumors in medical images have been implemented in the literature. These models can be divided into three main categories; multi-atlas registration (MAS) algorithms, ML approaches, and deep learning methods.

MAS is based on recording and combining the label of several normal brain atlases into a new image modality (Tang, Ahmad, Yap, & Shen, 2018). These MAS algorithms have not been successful with applications that require speed. ML approaches are mainly categorized using handmade features (or predefined features) (Le & Mikolov, 2014). As the first step, key information is extracted from the input image using some feature extraction algorithms, and then a model for recognizing the tumor from normal tissue is taught. Designed ML techniques typically use handmade features with different classifiers, such as random forest (Chen, Li, Shi, Rekik, & Pan, 2020), support vector machine (SVM) (Jalalifar, Soliman, Ruschin, Sahgal, & Sadeghi-Naini, 2020), and fuzzy clustering (Khosravanian, Rahmanimanesh, Keshavarzi, & Mozaffari, 2021). Designed methods and attribute extraction algorithms must extract attributes, edge details, and other necessary information — which is time-consuming. In addition, these methods show poorer performance when the boundaries between healthy tissues and tumors are vague/fuzzy. Deep learning methods automatically extract important features. These approaches have yielded outstanding results in various fields of application. Some studies identify the area of the tumor; paper (Havaei et al., 2017) which found the location of the tumor with the help of segmentation. Many researchers have manually adjusted the model hyperparameters. In the paper (Chato & Latifi, 2017), with the help of trial and error and manual adjustment, 90% accuracy in cancer diagnosis has been reached. However, the answers did not reach their optimal result and accuracy in the conventional methods.

In both conventional machine learning and deep learning approaches, meta-heuristic algorithms may increase classification accuracy. For example, in the Mehnatkesh et al. (2020), with the help of the genetic algorithm (GA), it was possible to increase the accuracy of the deep neural network model to 94%. One of the most important and efficient meta-heuristic algorithms is the ant colony algorithm (ACO). Studies and observations on ant colonies inspire the ACO. These studies have shown ants are social insects that live in colonies and their behavior is more for the survival of the colony than for the survival of a part of it. One of the most important and interesting behaviors of ants is their behavior to find food, especially finding the shortest path between food sources and nests.

This paper improves this algorithm. By improving this algorithm, the ability to exploit and explore is improved and the ability to find the global optimal is increased.

This paper aimed to investigate different MRI imaging methods to classify brain tumors and provide an optimal framework for obtaining a model with the best hyperparameters. For this purpose, in the first stage, images are pre-processed with the help of various image processing techniques. In the second step, the model with the best result for our data set is selected from the pre-trained models, and in the last step, six well-known optimization methods (ACO, PSO, GWO, GA, DE and BBO) are applied to the selected pre-trained model to obtain an optimal model. Finally, to provide an efficient technique for classifying brain tumors using MRI images through machine learning approaches, this paper presents a new approach that makes the model the best and the average accuracy to 99.02% and 98.69% respectively. The proposed approach is an improved ant colony method (IACO).

In summary, the main contribution of the current study can be summarized as follows:

We introduced a new evolutionary strategy for solving hyperparameter optimization of deep-learning based ResNet algorithm, which automatically selects the optimal set of hyperparameters for brain tumor classification problem.

In this paper, we propose a new and improved version of evolutionary ant colony algorithm called as IACO to improve the convergence speed and mitigate exploring the local optima.

Comprehensive experimental findings demonstrate the superior performance of our proposed IACO-ResNet model for deep neural network hyperparameter optimization.

The motivation of this paper is to obtain the best structure with the best hyperparameter using a new method for the brain tumor MRI dataset. Since achieving high accuracy in the classification of cancer has great importance in the treatment of the disease, this paper discussed seven pre-trained structures and seven well-known metaheuristic optimization methods and aimed to investigate different MRI imaging methods to classify brain tumors and provide an optimal framework for obtaining a model with the best hyperparameters and tried to make the final accuracy of the classification of the type of the disease as high as possible.

The following sections of this paper are organized as follows. First, all methodology is introduced in Section 2 which includes pre-processing and combination of the novel IACO with ResNet. Second, pre-trained and metaheuristic models are introduced in Section 3. Third, Section 4 is discussed the development and analysis of experimental testing and the performance of models is compared in this section too. Finally, the discussion and conclusion are presented in Sections 5 Discussion, 6 Conclusion.

Conclusion

This paper provides an accurate and fully automated system with minimal preprocessing to optimize the concept of deep transfer learning in brain tumor classification. The proposed method uses deep transfer learning to extract features from brain MR images with optimized hyperparameters to achieve an accurate model. For this purpose, seven pre-trained models for brain tumor datasets were taught, from which the ResNet was selected for optimization because it has the highest Best accuracy. TheCRediT authorship contribution statement

Hossein Mehnatkesh: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. Seyed Mohammad Jafar Jalali: Methodology, Software, Writing – original draft, Writing – review & editing. Abbas Khosravi: Writing – original draft, Project administration. Saeid Nahavandi: Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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٧* Using U-Net network for efficient brain tumor segmentation in MRI images

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Abstract

Magnetic Resonance Imaging (MRI) is the most commonly used non-intrusive technique for medical image acquisition. Brain tumor segmentation is the process of algorithmically identifying tumors in brain MRI scans. While many approaches have been proposed in the literature for brain tumor segmentation, this paper proposes a lightweight implementation of U-Net. Apart from providing real-time segmentation of MRI scans, the proposed architecture does not need large amount of data to train the proposed lightweight U-Net. Moreover, no additional data augmentation step is required. The lightweight U-Net shows very promising results on BITE dataset and it achieves a mean intersection-over-union (IoU) of 89% while outperforming the standard benchmark algorithms. Additionally, this work demonstrates an effective use of the three perspective planes, instead of the original three-dimensional volumetric images, for simplified brain tumor segmentation.

Introduction

Tumors are groups of cells which form abnormal tissue or growths within the human anatomy. Tumors can either be malignant where the growth is cancerous and will invade surrounding cells, or benign where the suspected growth is not cancerous [1]. Manual identification of these abnormal growths in human anatomy is not only onerous but might also be difficult from the perspective of a medical physician. Hence, the need for intelligent systems which can automatically detect the presence of cancer in a desired region of the human body [2], [3]. With the advancement of technologies in the medical field, there has been a tremendous impact on diagnostics and predictive analysis of diseases. We observe an advancement of healthcare analysis in brain tumor segmentation, heart disease prediction [4], stroke prediction [5], [6], identifying stroke indicators [7], real-time electrocardiogram (ECG) anomaly detection [8], and amongst others.

Brain tumors are such abnormal growths found within the human cranium. Given the complex and sensitive nature of the brain, a non-invasive technology, i.e. Magnetic Resonance Imaging (MRI), is the most popular pick for brain tumor diagnosis. These images are three-dimensional scans of a patients brain and can be visualized on either of its three respecting image planes (Coronal, Sagittal and Transversal), as shown in Fig. 1 [9]. Each perspective plane displays its information regarding a potential abnormal growth within the cranium. This classification of MRI scans based on the perspective planes has been noted to improve the analytical results while detecting brain tumors [10].

Brain tumor segmentation aims to autonomously and accurately identify the size and location of a brain tumor from MRI scans. While traditional machine learning techniques require hand crafted features to perform well, most of the current research is focused on using deep learning networks to segment a region of interest (ROI) from an input image. Although considerable success has been achieved using deep learning, they either require large amounts of annotated data [11] or they depend on aggressive data augmentation techniques [12]. However, a lightweight approach is almost always preferred for practical implementations [13], [14]. To this end, this paper1 makes the following key contributions:

The paper demonstrates an effective use of the three perspective planes, instead of the original three-dimensional volumetric images, for simplified brain tumor segmentation

A lightweight implementation of U-Net is proposed to provide accurate real-time segmentation

The proposed model is systematically benchmarked with several widely used segmentation algorithms.

The remainder of this article is organized as follows. Section 2 discusses existing image segmentation techniques that are frequently used in the domain of medical imaging. Also, in this Section we introduce the four algorithms which were chosen for benchmarking purposes in this paper. Section 3 follows up with the introduction of the dataset which is used in this study, and the pre-processing operations which were performed on the images. In Section 4, the proposed methodology is discussed in detail. The results are then discussed in Section 5, alongside a detailed comparison with the benchmarking algorithms. Lastly, Section 6 concludes the paper by summarizing the novelty, impact and obtained results.

Conclusion

Due to the purpose of our study, we have seen how U-Net an existing deep learning architecture for biomedical image segmentation can be altered and fine-tuned for brain tumor segmentation. By using the BITE's dataset and converting these three-dimensional MRI brain scans to two-dimensional images we have been able to use this data to evaluate the performance of a very lightweight implementation of U-Net which can accurately segment anomalies from two-dimensional images. The network outperforms any of the standard benchmarking algorithms used to evaluate the performance of the network, the network yields an average mean IoU of 84% when trained on the entire dataset, interestingly the mean IoU does not stagnate when the network is trained only on one the three perspective planes, a study which was undertaken to observe U-Nets approach to segmenting anomalies on small datasets containing less than one hundred images.

Our implementation of U-Net is lightweight and can perform accurate segmentation's, without the need for aggressive data augmentation. This proposed network could be used in a medical setting for trained physicians to have a second evaluator to a patients MR image. Research on the particular topic of brain tumor segmentation has advanced rapidly with the application of deep learning, however, more studies are needed to further improve the performance of a proposed network as the ratio between the predicted images False Negatives and False Positives is crucial in biomedical image analysis. We intend to benchmark our proposed lightweight U-Net with the original U-Net structure and other statistical [46] and deep learning networks [18]. Future work could improve on this performance by investigating the use of data augmentation to artificially increase the size of the dataset using an augmentor pipeline. Nevertheless, this study has shown how deep learning and computer vision can be applied in a medical domain to accurately segment brain tumors from two-dimensional MR brain images using a lightweight variant of a well known architecture.

Declaration of Competing Interest

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Analyzing the impact of feature selection on the accuracy of heart disease prediction

^* MRI-based brain tumour image detection using CNN based deep learning method

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Abstract

Introduction

In modern days, checking the huge number of MRI (magnetic resonance imaging) images and finding a brain tumour manually by a human is a very tedious and inaccurate task. It can affect the proper medical treatment of the patient. Again, it can be a hugely time-consuming task as it involves a huge number of image datasets. There is a good similarity between normal tissue and brain tumour cells in appearance, so segmentation of tumour regions become a difficult task to do. So there is an essentiality for a highly accurate automatic tumour detection method.

Introduction

Medical imaging refers to several techniques that can be used as non-invasive methods of looking inside the body [1]. The main use of medical image in the human body is for treatment and diagnostic purposes. So, it plays a significant role in the betterment of treatment and the health of the human.

Image segmentation is a crucial and essential step in image processing that determines the success of image processing at a higher level [2]. In this case we have mainly focused on the segmentation of the brain tumour from the MRI images. It helps the medical representatives to find the location of the tumour in the brain easily. Medical image processing encompasses the utilization and exploration of 3D image datasets of the physical body, obtained most typically from computed tomography (CT) or Magnetic Resonance Imaging (MRI) scanner to diagnose pathologies or guide medical interventions like surgical planning, or for research purposes. Medical image processing is applied by radiologists, engineers, and clinicians to understand the anatomy of either individual patients or population groups highly. Measurement, statistical analysis, and creation of simulation models which incorporate real anatomical geometries provide the chance for more complete understanding, as an example of interactions between patient anatomy and medical devices.

Tumour: The word “Tumour” is a synonym for the word “neoplasm” which is formed by an abnormal growth of cells. A tumour is significantly different from cancer [3].

1.1. Classification of tumour
1.2. There are three basic types of tumours: 1) Benign; 2) Pre-Malignant; 3) Malignant (cancer can only be malignant) [4].

1.1.1. Benign tumour

A Benign Tumour is not always Malignant or cancerous. It might not invade close tissue or unfold to alternative components of the body the way cancer can. In most cases, the outlook with benign tumours is not at all serious but it can be serious if it presses on vital structures such as blood vessels or nerves.

1.1.2. Pre-Malignant tumour

In these tumours, the cells are not cancerous. However, they need the potential to become malignant. The cells will grow and unfold to alternative components of the body.

1.1.3. Malignant tumour

Malignancy (mal- = “bad” and ignis = “fire”) Malignant tumours area are cancerous. They develop once cells grow uncontrollably. If the cells still grow and unfold, the malady will become dangerous. Malignant tumours will grow quickly and unfold to alternative components of the body during a method known as metastasis.

A latest research [5] in the year 2021 says that in United States among 24530 adults (13840 men & 10690 Women) will be identified with cancerous tumours of brain and in the spinal cord. A person's probability of developing this type of brain tumour in their lifespan is less than 1%. It causes 85% to 90% of all primary central nervous system (CNS) tumours. A number of 3,460 children under the age of 15 will also be identified with a brain or CNS tumour this year, other than this deals with adult primary brain tumours. Brain and alternative system nervous cancer is the tenth leading reason behind death for men and women. It is evaluated that 18,600 adults (10,500 men & 8,100 women) may die from primary cancerous brain and CNS tumours in the year 2021. Hence it's important to improve the accuracy of previously proposed methods for the betterment of medical image research. In our paper, our proposed 99.74% accurate CNN-based algorithm will help medical representatives in their treatment job without manually analyzing the MRI images so that the treatment speed can be enhanced.

Conclusion

MRI is most vastly used for tumour segmentation and classification. Although, convolutional neural networks (CNN) have the advantage of automatically learning representative complex features for both healthy brain tissues and tumour tissues directly from the multi-modal MRI images, so we decided to improve its accuracy. First we tried to implement SVM on CNN, but we got low accuracy of only 20.83%. Then we tried different parameters. We changed the final layer parameter to softmax and optimizer to AdaMax. Then we got 98.10% accuracy. But we need more, so we decided to change the optimizer to RMSProp, and finally we got the output accuracy to 99.74%. By using 2473 numbers of image as training data and 273 images for testing in 9:1 ratio with 11 epoch procedure we ultimately got our final result. Our model has 9 layer CNN model with 14 stages. Most importantly we also deleted some images to overcome overfitting.

Declaration of Competing Interest

We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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٩* Performance analysis of machine learning algorithm of detection and classification of brain tumor using computer vision

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Abstract

Brain tumor is one of the undesirables, uncontrolled growth of cells in all age groups. Classification of tumors depends no its origin and degree of its aggressiveness, it also helps the physician for proper diagnosis and treatment plan. This research demonstrates the analysis of various state-of-art techniques in Machine Learning such as Logistic, Multilayer Perceptron, Decision Tree, Naive Bayes classifier and Support Vector Machine for classification of tumors as Benign and Malignant and the Discreet wavelet transform for feature extraction on the synthetic data that is available data on the internet source OASIS and ADNI. The research also reveals that the Logistic Regression and the Multilayer Perceptron gives the highest accuracy of 90%. It mimics the human reasoning that learns, memorizes and is capable of reasoning and performing parallel computations. In future many more AI techniques can be trained to classify the multimodal MRI Brain scan to more than two classes of tumors.

Introduction

Computer Aided Diagnosis (CAD) is one of the major contributions of technology implemented in the field of medical science for better precision and high accuracy. It is considered as a high throughput for the expediency to investigate the outgrowth expanse. The implementation of technology, diagnosis and treatment planning becomes easy and gives the physician a second taught of his predictions. The most dominant tool for imaging the brain is the Magnetic Resonance Imaging (MRI) which are multimodal, where in these modalities can reveal different parts in the tumor, and provides information concomitant to anatomical assemblies as well as potential anomalous tissues essential for diagnosis and treatment planning [1,2]. The different sequences like the T1 weighted, T2 weighted, Fluid Attenuation Inversion Recovery (FLAIR) and Diffusion Weighted Imaging (DWI) show the different intensity variations that help in identifying the region of interest. Extracting reckonable data from MRI helps to capture the functions of different consequence crevices in case of different types of tumors. The possibility of survival of a patent is increased if the tumor is perceived at an early stage. However precise segmentation and categorization of abnormalities are not forthright. There exist a number of semiautomatic and fully automatic methods for the classification of tumors but clinical acceptance depends on simplicity and less human intervention. Classification of tumors in the human brain is possible by implementing the Supervised Machine Learning techniques, in this research we work upon the Naïve Bayes, The Logistic, Multilayer Perceptron (MLP), The Support Vector Machine (SVM) and the Decision Tree (DT) for classification and the results are compared on the basis of classification accuracy for the data used. Classification is performed with more discriminative features initially on the OASIS and ADNI [3,4] database

Yet there are some challenges to be addressed for classification of abnormalities in medical imagining like selection of appropriate model, describing the given data, finding the errors in the data, the adequacy of data used and confidence about the results. Therefore, there is no universal recognized method for medical image classification. So, it remains a challenging problem in computer vision and Machine learning. Fully automatic systems determine the tumor part without human intervention these systems generally include human intelligence and prior knowledge about the throughput. These algorithms which are mostly developed by using soft computing and model-based techniques prove to produce accurate results. The study of automatic brain tumor classification represents interesting research in Machine Learning and Artificial intelligence (AI)

The organization of this paper is as follows. In Section II, the existing scientific research in medical image classification is reviewed, along with the motivation for this research. Section III presents the materials and methods used in this work it describes the dataset implemented, it also shows the proposed work. Section IV, represents the experimental results obtained and finally the section V, elaborates the outcomes and conclusion.

Conclusion of the research

This research shows the state-of-art methods for classification of the tumor as cancerous and non-cancerous (Benign and Malignant). The advantage here is that it does not need any prior information about the probability distribution of different classes. Logistic and MLP are the branches of Machine learning that learns, and performing parallel computations. The most advantageous part in applying ML model is that the result of the system does not depends on the dataset and the structure of the

Declaration of Competing Interest

The authors declare that we have no conflict of interest.

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۱۰* Brain Tumor Imaging: Applications of Artificial Intelligence

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Abstract

Artificial intelligence has become a popular field of research with goals of integrating it into the clinical decision-making process. A growing number of predictive models are being employed utilizing machine learning that includes quantitative, computer-extracted imaging features known as radiomic features, and deep learning systems. This is especially true in brain-tumor imaging where artificial intelligence has been proposed to characterize, differentiate, and prognostication. We reviewed current literature regarding the potential uses of machine learning-based, and deep learning-based artificial intelligence in neuro-oncology as it pertains to brain tumor molecular classification, differentiation, and treatment response. While there is promising evidence supporting the use of artificial intelligence in neuro-oncology, there are still more investigations needed on a larger, multicenter scale along with a streamlined and standardized image processing workflow prior to its introduction in routine clinical decision-making protocol.

Introduction

Artificial intelligence (AI)-based analysis of imaging data has revolutionized the field of noninvasive biomarker discovery. It relies on using radiologic images as mineable databases with quantitative radiomic or texture features that can be learned and/or predict clinically significant output.1 Machine learning (ML) and deep learning are subsets of AI, each with unique qualities that allow for computerized image analysis.

Radiomics is most currently described as the "high-throughput extraction of quantitative features that result in the conversion of images into mineable data and the subsequent analysis of these data for decision support."2 While the concept of data mining is not novel, and nor is it based in AI, the recent advances in ML has made possible radiomic feature extraction with subsequent image analysis. More specifically, ML can extrapolate the mined data to produce clinically significant prediction models and classifiers through computer algorithms.1 While the scope of this article centers around the use of AI in neuro-oncology imaging, the combination of radiomics and AI is applicable to a wider range of systems and pathology.

Radiomics can be further subdivided into feature-based or deep learning-based radiomics, based on the method of radiomic feature acquisition. In feature-based radiomics, predetermined features are mathematically extracted from specific region-of-interest (ROI) and are commonly referred to as "handcrafted" or "hand-engineered" features.1 These radiomic features are then selected based on feature selection algorithms. In contrast, deep learning-based radiomics involves training computer models from the generated data, through learning algorithms and advanced statistics, to extract pertinent radiomic features.3 It stands to reason that feature-based radiomics is limited by finite mathematics-based relations when compared to deep learning-based radiomics, which is continuously refined with each data entry. Handcrafted features also require standardization of technique, image preprocessing and ROI selection, leaving it exposed to variations in image acquisition, data analysis and generalizability. Due to the predetermined nature of handcrafted features, they are better suited for smaller data sets, which could explain their prevalence in literature.

Deep learning-based radiomics seeks to imitate the function of the human brain by using artificially constructed neural networks. These neural architectures, such as convolutional neural networks (CNNs) find the most relevant features from the input data, which are used for pattern recognition or the classification of nonlinear data. Individual neural layers with linear/nonlinear activation functions learn the representation of imaging data with various levels of abstraction, after which the layers are then stacked and connected for classification and output.4 Each hidden layer within the network is responsible for data from 1 level - for example, the first level may represent edges in an image oriented in a specific direction, while the second layer could be responsible for motif detection in the observed edges, and the third could recognize objects from the ensembles of motifs.5 The extracted features can be processed by the network itself for analysis of performance and classification, or they can undergo model generation through a similar process as feature-based radiomics by using different classifiers such as support vector machines (SVM), regression models or decision trees.3 While feature-based radiomics requires image preprocessing, the opposite might be true for deep learning as standardization may have a negative impact by removing information. Due to the self-learning aspect of deep neural networks, it is more likely to have poor performance on smaller datasets, which is one of the reasons that most studies utilize feature-based radiomics to test their hypothesis.1

Conclusion

Section snippets

Characterization of Brain Tumors

Over 150 different brain tumors have been described based on histopathological characteristics. The gold-standard for their characterization requires histopathological analysis by retrieving tumor samples from biopsy.6 However, due to the heterogeneity of some tumors, their inaccessible location, or the patient's clinical status, noninvasive radiological characterization of the brain tumors will be ideal. AI is a promising tool that serves to compliment, and possibly replace, the need for

Prognostication

We have discussed the utility of AI in predicting molecular biomarkers such as IDH mutation, 1p/19q codeletion, and MGMT promoter methylation status, and their effects on patient prognosis. In this section, we highlight studies conducted by groups that evaluate the use of other prognostic markers in ML to determine prognosis of patients with brain tumors, particularly GBM, which is the most common and most aggressive primary brain tumor with a median survival between 12 and 15 months.65

Prasanna

True Progression (TP) vs Pseudoprogression (PsP)

Pseudoprogression (PsP) refers to treatment-related changes that mimic the true progression (TP) of posttreatment GBM. This occurs primarily within the first 6 months after completion of treatment, which includes surgical excision and chemoradiation with temozolomide. Accurate differentiation between TP and PsP is essential for assessing response to treatment and patient prognosis. This section reviews the role of ML in differentiating TP from PsP.75

Many groups have investigated the role of

Limitations and Future Considerations

Early evidence for the use of ML in clinical practice shows great promise, however there are limitations that prevent it from becoming a routine part of clinical work up. One of the factors limiting the routine use of ML is the burdensome process of image segmentation. There is no reliable and automated tumor-segmentation algorithm currently used, and few studies have significant validation for their attempts at automation of tumor segmentation. Future studies should look to develop such

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