Proceedings of the 5th International Conference on Computing and Data Science
DOI: 10.54254/2755-2721/16/20230891

The study and application of brain tumors classification based on artificial intelligence

Rongzhao Peng

School of Software, South China Normal University, Guangzhou, 510631, China

20202005211@m.scnu.edu.cn

Abstract. The application of AI in the medical field has been increasingly popular due to its ability to enhance the accuracy and efficiency of diagnoses. A plurality of individuals employs diverse techniques and refine existing methods in order to achieve greater precision. This paper provides an overview of the methodology utilized in early research papers for brain tumors classification. This includes the input of datasets, preprocessing, model building, training and testing, evaluation, and application. In addition, this paper presents four models used in early research, including the Artificial neural network (ANN) which mimics the organization and operation of neural networks in living organisms by processing information through interconnected nodes or neurons. Another model is k-Nearest Neighbor (KNN), an instance-based learning algorithm that labels new data points by comparing them to the K closest labeled data points in the training dataset. The third model is Visual Geometry Group-16 (VGG-16), a 16-layer Convolutional Neural Network (CNN) that is highly regarded for its simplicity and effectiveness and is one of the top-performing CNN models used by VGG. Lastly, GN-AlexNet is a hybrid learning mode that combines the GoogleNet structure with the AlexNet model. The remainder of the article explains the utilization of this AI in three application scenarios, namely as an assistant for doctors, patients, and insurance companies. Moreover, the paper highlights potential challenges that may arise in both the present and future, such as patient mistrust and the emergence of new models like Vision Transformer (ViT) that could potentially outperform CNNs.

Keywords: AI, brain tumors, CNNs, deep learning.

1. Introduction

Brain tumors manifest as either benign or malignant, depending on the nature of the abnormal cell growth [1, 2]. Benign tumors grow slowly and have a low likelihood of spreading to other parts of the body after treatment. Nevertheless, malignant tumors are made up of cancer cells and have the ability to invade tissues locally or spread to different parts of the body, a process which are named metastasis [1]. On There were 83,029 deaths because of malignant brain and other CNS tumors between 2014 and 2018, and this reveals an average of 16,606 deaths per year [3]. Magnetic Resonance Imaging (MRI) is the most common method used to differentiate between tumor types. However, this method is easily affected by human subjectivity, and can be challenging for human due to the large amount of data involved. As a result, detecting brain tumors at an early stage often relies on the radiologist's expertise [4]. To achieve accurate diagnosis and minimize subjectivity, it is essential to develop an effective diagnostic tool for segmenting and classifying tumors from MRI images [5]. Artificial intelligence (AI) has the potential to address these issues and could be utilized to classify brain tumors, offering a solution for accurate diagnosis and timely treatment.

Glioma tumors arise from mutations in glial cells that cause normal cells to become malignant. They are the most prevalent form of astrocytoma, a type of brain or spinal cord tumor. Glioma tumors make up 30% of all tumors in the brain and central nervous system and 80% of all malignant tumors [5]. Therefore, identifying glioma tumors is crucial in determining whether patients have a brain tumor or not. In 2009, Zacharaki et al. proposed a framework for identifying glioma, which can achieve a precision of 85% for multiple classifications and 88% accuracy for binary identification [6]. In 2010, El-Dahshan et al. proposed a method for identifying 80 brain tumor images, both abnormal and normal. They used the Discrete Wavelet Transform (DWT) technique for feature extraction and Principal Component Analysis (PCA) for feature reduction. They then used Artificial Neural Network (ANN) and k-NN to classify the images with an accuracy of 97% and 98%, respectively [7,8]. With significant advancements in computer performance and the development of neural network theory, as well as the introduction of Convolutional Neural Networks (CNNs), deep neural networks have demonstrated a strong advantage in image analysis tasks, including the analysis of brain tumor. In recent years, CNNs have become increasingly popular for classifying brain tumors due to their high accuracy and outstanding performance in research settings [9,10]. In 2017, Healthy, low-grade glioma, and high-grade glioma are the three categories into which Khawaldeh et al. classified brain MRI images. By utilizing 4069 brain MRI images, they were able to fulfill an overall accuracy of 91.16%. [11]. Rehman et al. proposed in 2020 to use multiple pre-trained CNN models, namely AlexNet, GoogleNet, and VGG16, to classify brain tumors into glioma, meningioma, and pituitary. They employed 3064 brain MRI images that were gathered from 233 patients. The VGG-16 model accomplish the best classification accuracy of 98.69% during this transfer learning approach [12]. In 2022, an accuracy of 99.51% was accomplished by Samee N A et al. when they designed a transfer learning approach that integrates multiple models called GN-AlexNet for classifying brain tumour [13].

The following is an outline of the organization of the rest of this chapter. The methods section provides a detailed introduction to recent papers on how to use CNNs to classify brain tumors. Furthermore, Section 3 covers the application of these algorithms and examines the future challenges in the field of CNNs for brain tumor classification. Finally, Section 4 concludes the paper by summarizing the content and presenting conclusions drawn from the previous papers.

2. Methods

2.1. Overview

The methods are outlined in a manner similar to that shown in Figure 1. After building an image database and setting the image label, the preprocessing of these images is the key to feature extraction by image reduction and enhancement. By downsizing and converting images to grayscale, the model training time can be reduced, and the speed of model inference can be increased [8]. Image enhancement methods such as linear, nonlinear, fixed, multi-scale, and pixel-based are used in different circumstances [2]. Feature extraction can be performed using techniques such as DWT and PCA. [7]. The preprocessed data and image label are used as inputs for the neural network [13]. Next, building the models outlined in this paper, which are categorized into traditional models (i.e., ANN, KNN) and CNNs models (i.e., AlexNet, GoogleNet, and VGG16). After model training and testing, the program is executed, and its resulting output is evaluated accordingly.

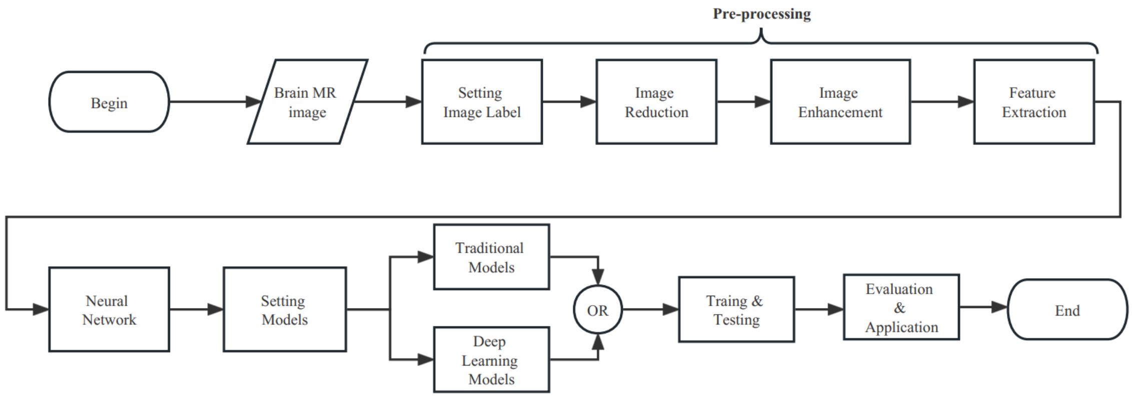

Figure 1. The common procedure of the method used in the brain tumor recognition.

2.2. Models

2.2.1. ANN. ANN is a computational system that mimics the architecture and operation of biological neural networks. It is made up of interconnected nodes or neurons that process information using a connection approach. They utilized the Levenberg-Marquardt training function, known for being the fastest, in the construction of the neural network. According to their paper, this function yields faster and more accurate results compared to other functions they have mentioned. The ANN initially undergoes a learning process and subsequently makes predictions in the testing phase. The ANN is composed of three primary layers: the input layer, the hidden layer, and the output layer [14].

2.2.2. KNN. K-Nearest Neighbor (KNN) is a type of instance-based learning algorithm that assigns labels to new data points by referring to the majority label among the K-nearest data points in the training dataset. It determines the similarity between data points based on their proximity and uses the labels of the closest neighbors to make a prediction. Karuppathal et al. enhanced the Fuzzy KNN algorithm, which is a two-stage clustering method. The first stage calculates the centroid using KNN, while the second stage computes fuzzy-based membership [15].

2.2.3. VGG-16. The Visual Geometry Group- 16 (VGG-16) model is a 16-layer CNN that is highly regarded for its simplicity and effectiveness. It is one of the top-performing CNN models used by the VGG. Ayesha To detect brain tumors, Younis et al. employed the VGG16 CNN model framework and the model's weight in order to train their data. The VGG16 model employs small (3x3) convolution filters throughout its entire network and requires a minimum input image size of 224x224 pixels with three channels. By using small filters and multiple layers, the VGG16 architecture, which comprises 16 layers including 13 convolutional and 3 fully connected layers, can acquire hierarchical representations of the input data. This design enables the network to capture intricate features from the input data while maintaining a relatively low number of parameters. Compared to traditional approaches, their findings demonstrated that the suggested network structure was attractive and excelled in identifying tumors [16].

2.2.4. GN-AlexNet. The GoogleNet model has garnered attention in the medical imaging classification and grading field due to its ability to work with raw images and achieve improved classification. Additionally, knowledge transfer models such as AlexNet layers are frequently employed to extract features. Samee et al. enhanced the CNNS model by merging the GoogleNet structure with the AlexNet model. By eliminating five layers from GoogleNet and incorporating ten layers from AlexNet, they created a new model called GN-AlexNet which automatically extracts and classifies features. The GN-AlexNet learning model comprises multiple layers, where the initial step in processing images involves feeding them into the input layer. The images then move to a convolutional layer where an operation in

DOI: 10.54254/2755-2721/16/20230891

mathematics is performed using two inputs. The resulting feature map is generated by multiplying the input image with the filter [13].

3. Application and discussion

3.1. Diagnosis Virtual Assistant

CNNs have demonstrated significant potential in improving the accuracy and efficiency of brain tumor classification, and can be integrated into diagnostic tools to assist doctors in making informed decisions. Moreover, patients can benefit from personalized advice and support regarding their brain tumor diagnosis and treatment by uploading their own brain MRI images online through AI-powered virtual assistants. These virtual assistants can aid patients in managing their symptoms and monitoring their progress over time, even when they are not in the hospital. Such assistance can enable patients to gain a better understanding of their illness. In addition, insurance companies can utilize these technologies to conduct appropriate risk assessments for their customers. By analyzing vast amounts of data related to their customers' health, AI-powered tools and virtual assistants enable them to accurately evaluate the risks associated with providing coverage to each customer. For instance, the insurance company may adjust their coverage or premiums based on whether a customer's brain tumor is malignant or benign, using this information gleaned from the data analysis.

3.2. Challenges

Despite the significant progress made in the integration of AI into clinical practice, there are still obstacles that must be overcome. A key challenge is patient trust and confidence in the use of AI. While AI has been demonstrated to outperform human performance in some medical applications, patients may still feel hesitant to rely solely on AI for diagnosis and treatment decisions. Therefore, further research and development is necessary to improve the integration of AI into clinical practice and to address patient concerns. Furthermore, although CNNs have achieved remarkable success, they typically exhibit inductive biases, such as the local receptive field's translation equivariance. These biases can hinder the models' ability to learn long-range information effectively, and as a result, data augmentation is often necessary to enhance CNNs' performance. This is because CNNs rely heavily on local pixel variations during the learning process. Compared to CNNs, attention-based transformer networks have the advantage of being able to focus more on global features. In fact, a variant of the transformer architecture called the Vision Transformer (ViT) has been suggested for image analysis and has demonstrated superior performance to CNN models in large datasets. However, since ViT is a relatively new development in the medical field, there is currently a lack of sufficient data to train and validate its performance [17]. This represents a challenge for its adoption and highlights the need for further research and development to address this issue.

4. Conclusion

The article presents a summary of the approach employed in the initial research studies for classifying brain tumors, which involved the utilization of various AI techniques such as ANN, KNN, VGG-16, and GN-AlexNet. Furthermore, the article presents a brief history of AI's involvement in this field. Additionally, the paper outlines the potential applications of CNNs in brain tumor classification, such as assisting physicians in diagnosis, educating patients about their condition, and enabling insurance companies to perform accurate risk assessments for their clients. The paper also sheds light on the challenges that may arise in the the present and the future such as patient mistrust and the emergence of new models like ViT that may outperform CNNs.

References

[1] Chatterjee S et al 2022 Classification of brain tumours in MR images using deep spatiospatial models (Scientific Reports)

DOI: 10.54254/2755-2721/16/20230891

[2] Amin J et al 2022 Brain tumor detection and classification using machine learning: a comprehensive survey (Complex & Intelligent Systems)
[3] Ostrom Q T Cioffi G Waite K et al. 2021 CBTRUS statistical report: primary brain and other central nervous system tumors diagnosed in the United States in 2014–2018 Neuro-oncology 23(Supplement_3) 105.
[4] Afshar P et al 2019 Capsule Networks for Brain Tumor Classification Based on MRI Images and Coarse Tumor Boundaries (International Conference on Acoustics, Speech and Signal Processing)
[5] Badža M M et al 2020 Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network (Applied Sciences)
[6] Zacharaki EI et al 2009 Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme (Magnetic Resonance in Medicine)
[7] Ahmed El-Dahshan E et al 2010 Hybrid intelligent techniques for MRI brain images classification (Digital Signal Processing)
[8] Mehrotra R et al 2020 A Transfer Learning approach for AI-based classification of brain tumors, Machine Learning with Applications (Machine Learning with Applications)
[9] Ozcan H et al 2021 A comparative study for glioma classification using deep convolutional neural networks (Mathematical Biosciences and Engineering)
[10] Xie Y et al 2022 Convolutional Neural Network Techniques for Brain Tumor Classification (from 2015 to 2022): Review (Challenges, and Future Perspectives)
[11] Khawaldeh S et al 2018 Noninvasive Grading of Glioma Tumor Using Magnetic Resonance Imaging with Convolutional Neural Networks (Applied Sciences)
[12] Irmak E et al 2021 Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework (Iranian Journal of Science and Technology Transactions of Electrical Engineering)
[13] Samee N A et al 2022 Classification Framework for Medical Diagnosis of Brain Tumor with an Effective Hybrid Transfer Learning Mode (Diagnostics)
[14] A Biswas et al 2021 Brain Tumor Types Classification using K-means Clustering and ANN Approach (International Conference on Robotics Electrical and Signal Processing Techniques)
[15] Karuppathal R et al 2014 Fuzzy based automatic detection and classification approach for MRI-brain tumor (Computer Science)
[16] Younis A et al 2022 Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches (Applied Sciences)
[17] Tummala S et al 2022 Classification of Brain Tumor from Magnetic Resonance Imaging Using Vision Transformers Ensembling (Current Oncology)