The Use of Artificial Intelligence Models in Brain Tumor Classification

Binghe Feng *

Shanghai Pinghe School, Shanghai, China

* Corresponding Author Email: fengbinghe2022@outlook.com

Abstract. Brain tumor classification is very important for clinical diagnosis, but traditional methods like biopsy (which is invasive) and spectroscopy (which is expensive) make it hard to do well. Artificial Intelligence (AI) has become a helpful tool here, using medical images to make classification more accurate and efficient. This paper reviews AI models used for brain tumor classification. It looks at two main types: traditional machine learning models and deep learning models. The paper explains how these models work and finds that deep learning models usually work better than traditional ones because they can learn directly from data without extra manual steps. However, there are still problems. AI models, especially deep learning ones, are like “black boxes”. It is hard to understand how they make decisions. Also, they may not work well in real hospitals because of inconsistent medical records or limited equipment. What’s more, using patients’ sensitive data to train these models risks privacy leaks. Future research should add doctors’ professional knowledge to AI, help models adapt to different hospital settings, and use methods like federated learning to protect privacy. In short, AI has great potential in brain tumor classification, and solving these problems will help it be used more in hospitals to improve diagnosis efficiency.

Keywords: Brain tumor classification, artificial intelligence, machine learning.

1. Introduction

A brain tumor is commonly referred to as an abnormal growth or mass of cells in or around the brain [1]. Despite its relative rarity, with over 25000 Americans diagnosed in 2024, their mortality is extremely high, exhibiting a rate of approximately 70% [2]. Furthermore, there are more than 120 types of brain tumors, from brain cancers to benign tumors, which are different from the brain tissues they affect [3]. Artificial intelligence (AI), a rapidly developing technology, can extract subtle features in images and has the potential to assist doctors in improving diagnosis accuracy. Therefore, it is very worthwhile for professionals to create technology using artificial intelligence in classifying brain tumors.

Before the development of AI, most hospitals relied on biopsy or spectroscopy. These two approaches have obvious drawbacks. A biopsy involves invasive operations, which have many harmful effects on patients’ bodies. Although spectroscopy can directly reflect the biological characteristics of tumors, its equipment is expensive, and the data collection is complex. Thus, no particularly fast and precise brain tumor classification methods were available in the past.

After AI technology matures, some previous methods can be replaced by it. According to a current study of AI medical applications, people used Magnetic Resonance Images (MRI) and Computed Tomography (CT) to scan images as data. Computers employed filtering techniques to reduce image noise and adjust their brightness. Afterwards, they extracted the texture and shape features as inputs for an Artificial Neural Network (ANN). The ANN was designed to analyze processed data and, after accurate computations, match it with similar types of tumors in the database. There are some inevitable limitations to the model, which is that scientists should provide hundreds of different kinds of tumor pictures to the database to ensure correct classification, and the model cannot offer specific reasons [4]. In 2020, Gopal S. Tandel created another AI assistant, which was able to divide MRIs into 6 levels (level 1 to level 6) according to their severity. To evaluate its performance, he compared AI with the traditional methods, particularly Support Vector Machine (SVM). The SVM can only perform steadily in level 2 and level 4, with a classification accuracy rate of 88% and 72%

respectively, and only 65% in level 6, while the AI performed much higher than the traditional group in these three levels, 95%, 87%, and 89% respectively. Moreover, the doctor divided the MRI and other statistics into multiple components in order to verify that all the judgments made before were reliable. This new approach was proven to be both accurate and effective [5].

The aim of this paper is to provide a comprehensive review related to the application of artificial intelligence models in brain tumor classification. The remainder of the paper is organized as follows. First, this paper will focus on the types and principles of AI models employed in this field. Then, the challenges faced by AI models, along with strategies, will be discussed. Finally, the conclusion will be provided to summarize the whole paper.

2. The Types and Principles of AI Models

2.1. Traditional Machine Learning-Based Prediction

2.1.1. Decision Trees

Before 2010, traditional machine learning algorithms, including decision trees, random forests, and SVMs, were widely utilized in hospital settings. Janki Naik devised decision trees to classify brain tumors. The image was pre-processed using median filtering and morphological opening to improve its quality and remove unwanted distortions. The main features of the image were extracted and input into Apriori, a rule-mining algorithm designed to identify associations and patterns within large amounts of data. These rules were then used to create a classification system that could determine whether a brain tumor was normal, benign or malignant. The system used in the research was a decision tree, where internal nodes represented a test of an image feature, each branch corresponded to a test result, and each leaf node denoted an outcome. During the classification, image features are input, and the corresponding category is determined from the root to a leaf node [6].

2.1.2. Random Forests

Ashwani Kumar Aggarwal pioneered the development of a feature extractor known as the Gray-level Co-occurrence Matrix (GLCM) specifically for random forests. To standardize the GLCM, he employed four distinct formulas to compute the energy, heterogeneity, homogeneity, and contrast of each pixel within an image. These four parameters were subsequently input into the random forest model. This model has higher accuracy compared to a single decision tree because of its composition of multiple decision trees. Its randomness is reflected in the generation of N distinct sub-training sets derived from the original training sample. Each sub-training set is then used to train a single decision tree. When processing a new sample, all decision trees generate their predictions, and the final result is determined as the category that receives the majority of votes [7].

2.1.3. Support Vector Machine

Akhanda Nand Pathak has designed a system that uses SVM to classify brain tumors. First, the image is preprocessed as the input of the wavelet image. The wavelet image then observes every detail and feature on the tumor image by constantly adjusting the focal length. After the wavelet transformation, numerous features are obtained, and it takes a considerable amount of time for the computer to process them. To solve this problem, Principal Component Analysis (PCA) was developed. It can convert images into vectors and then calculate mathematical formulas, such as covariance matrices and eigenvectors. The model selects the most important components to represent the original data. The processed data is then input into the SVM, which can find the best line (or polyplanar, hyperplanar) to separate the two types of tumors. For example, in 2D, these tumor types form a circle, and when they are extended to 3D, they may be separated by a plane. Then, the dimension is reduced back, which is equivalent to finding a curve as a dividing line in the original dimension [8].

2.2. Deep Learning Models-Based Prediction

2.2.1. Artificial Neural Network

Since 2010, deep learning models have undergone rapid development. Angona Biswas achieved notable success in his research on ANNs. Firstly, he unified the pixel dimensions of MRI images. Subsequently, he employed a tool known as a "Sharpening Filter" to enhance the image clarity. Afterwards, he adjusted the contrast and brightness, thereby making the differences between tumors and surrounding tissues more distinct. Following this, he designed a K-means clustering algorithm to classify tumor regions from the surrounding background, which laid a solid foundation for later feature extraction. The scholar then utilized a two-dimensional discrete wavelet transform (2D-DWT) to extract features from multiple angles. Eventually, he constructed a feedforward neural network, which consisted of an input layer with 13 neurons, a hidden layer with 20 neurons, and an output layer with 3 neurons. For the training of the ANN, he adopted the Levenberg–Marquardt training function to boost classification accuracy. In terms of data allocation, 70% of the data was used for training, 15% for validation, and 15% for testing [9].

Dipali M. Joshi was another researcher involved in the application of ANN. She preprocessed MRI images using the same method as previous experts: filling gaps at tumor edges with filling operators to enhance the contrast, then extracting large tumor areas via morphological operations to improve the effectiveness of classification and analysis. She also used GLCM for feature extraction, and the processed data was fed into the computing nodes. Each node performs a weighted sum, where weights reflect feature importance. Key features for tumor diagnosis have high weights, and secondary ones have low weights. Since the relationship between brain tumor characteristics and classification is complex and non-linear, the weighted sum results need processing by non-linear activation functions like Sigmoid and ReLU. These functions simulate the non-linear transmission of biological neural signals and help the network learn such complex relationships. ANNs are adaptive, with adjustable parameters during training. This allows the network to change parameter settings for different textures, meeting the classification needs of various tumor types [10].

2.2.2. Convolutional Neural Network

Neha Sharma introduced the main components of Convolutional Neural Networks (CNN) and the classification steps. She presented the training steps and the main components of CNN. During the training, once image pre-processing is complete, the computer automatically reads the image from the folder and divides it into training sets and validation sets. It then downloads the VGG16 model (a type of CNN) and its weights. Finally, the optimizer, loss function and evaluation indicators are set up, and the model can start learning. CNN consists of an input layer, a convolutional layer, a rectified linear unit (ReLU), a pooling layer and a fully connected layer. The first two layers filter out specific features in the MRI image. The third layer changes negative values to 0 and keeps positive values, thereby enabling subsequent steps to run faster and introducing nonlinear factors that allow CNN to handle complex nonlinear problems. The fourth layer's primary function is to reduce the dimensionality of the feature map, thereby reducing the number of parameters and computational work in the network. The final layer uses complex calculations to produce the final classification results, and is key to enabling CNNs to perform classification tasks [11].

Muhammad Sajjad designed an improved and upgraded CNN model called the Input Cascade CNN. It runs almost 40 times faster than traditional CNNs. This model has 13×13 receptive fields. Firstly, the tumor-like spots near the skull are removed by the connected component labeling algorithm, so the segmented tumor area is obtained. Deep learning models require large amounts of high-quality data to ensure performance, and brain tumor MRI data has the problem of small sample sizes. In order to solve this problem, the study designed 8 data enhancement technologies, modified the two dimensions of geometry and noise, and expanded each original sample to 30 new samples, greatly increasing the amount of data. Finally, the VGG-19 CNN was selected for this study, and after inputting the processed data, it will gradually extract features through the convolutional layer and pooling layer, and finally generate a 1000-dimensional feature vector (compressed into a list of 1000 numbers, each number represents the intensity value of a key feature) through three fully connected layers, and then input it into the Softmax classifier, and finally output that the tumor belongs to grade I, grade II, grade III, or grade IV [12].

2.2.3. Vision Transformer

Ning-Yuan Huang designed an algorithm consisting of a Feature Pyramid Network (FPN) and a Vision Transformer (ViT). The FPN first examines the whole image at low magnification, extracting the most basic features, such as the edges of the tumor and small spots, and collecting these features. It will then take a high-powered magnifying glass to examine the details. For example, if a small spot is found, the overall information is used to determine whether it is a tumor or an ordinary tissue shadow. The tumor-affected area is then input into the ViT. The ViT first divides the medical image of the tumor into many small pieces, which makes subsequent analysis easier and faster. Then, it will analyze the relationship between each small piece and all the others. For example, if one piece looks like a tumor, the model will check whether the surrounding pieces also have tumor characteristics and make a comprehensive judgment [13].

3. Challenges and Future Prospects

3.1. Challenges

3.1.1. Interpretability

All deep learning models have one drawback in common: they are inexplicable. This is because they are all made up of complex neurons, which makes their internal structures abstract and difficult to understand. For example, the traditional system can derive diagnostic conclusions directly based on preset medical rules, enabling doctors to clearly trace the basis for each judgment step. Deep learning models, such as CNNs and Recurrent Neural Networks (RNNs), process raw data through multiple layers of non-linear neurons. Their feature extraction and decision-making processes are highly abstract, making it difficult for developers to fully explain why the model came to a certain conclusion. This is a typical "black box" characteristic [14].

3.1.2. Applicability

The core of AI's applicability in the medical field is whether the model can function reliably and stably in real clinical scenarios. However, deep learning models also have their limitations in clinical practice. For example, medical images rely on natural image model fine-tuning (for example, the light skin training model has low accuracy for dark skin recognition). The Electronic Health Record (EHR) code in different hospitals is not uniform, so the timing information is lost. Moreover, some physiological signal preprocessors are prone to losing key features, and equipment errors affect accuracy. The performance of laboratory tests is completely different from that of clinical applications. Most models suitable for laboratories are optimized for a single task and are difficult to adapt to the entire treatment process, for example, only detecting issues without providing treatment recommendations or identifying causes. This type of model is particularly poorly suited to special populations, such as children and patients with rare diseases. In some scenarios with limited resources, such as primary hospitals, there are usually only low-resolution devices, which significantly degrade performance [14].

3.1.3. Privacy

The challenge that all AI models need to face is security, and traditional AI model training needs to centralize data on a unified server, and if there are security problems in the storage system (such as hacker attacks, insider violations), it can lead to large-scale data breaches. For example, EHRs contain sensitive information such as patient names, ID numbers, and diagnostic results. Even if data is not directly shared externally, the model training process may indirectly compromise privacy. For example, an attacker can use reverse reasoning to infer whether a patient is in the training dataset, such as inputting a specific patient's EHR into the model and observing the relation between the output and the training data [14].

3.2. Future Prospects

3.2.1. Expert System and Domain Knowledge

The integration of experts and AI can solve the current problems of insufficient medical logic and a lack of experience in medical care. At present, most intelligent medical models rely on data training, but it is difficult to correlate with clinical guidelines and medical knowledge, and some unusual complex diseases are prone to misjudgment. In the future, experts will provide a structured knowledge graph to AI models based on medical rules (symptoms, medication contraindications), such as implanting symptoms and electrocardiogram (ECG) knowledge to reduce the possibility of misdiagnosis. At the same time, the decision tree model can be used to check whether the output diagnosis and treatment recommendations are correct. In addition, updating the knowledge database on time can avoid the problem of outdated diagnoses [15].

3.2.2. Domain Adaptation

In addition, domain adaptation has the potential to become an area of future research for intelligent AI models. This technology is known to exhibit a degradation in performance in the target domain (e.g., hospitals) after training in the source domain (e.g., the laboratory). For instance, a health monitoring model trained in a laboratory setting with constant temperature and a static environment, when deployed in the home environments of the elderly, may be susceptible to misjudging the heart rate and blood oxygen saturation. This susceptibility arises as a result of altered data collection conditions, including temperature fluctuations and interference from the elderly's daily activities. In order to resolve the issue, the researchers endeavored to install domain-adaptive technology on the model. This technology facilitates the transfer of learning across different scenarios, thereby enabling the model to rapidly adapt to new environments without collecting a substantial volume of scene data. The fundamental logic of the model is to facilitate the learning of differences between the source and target domains, to enable automatic adjustment of the feature extraction strategy, which can ensure stable performance and high accuracy [15].

3.2.3. Federated Learning

Federated learning will become a technology that balances the sharing of medical data with the security of patient privacy by AI models. The current performance of intelligent medical systems is highly dependent on large-scale and diverse medical data, but medical data has strong privacy and is also restricted by national laws and regulations. This technology enables data holders (e.g., hospitals and community centers) to retain the original data locally, with the institution uploading the missing parts of the model training process to a central server. The central server is responsible for updating the data provided by the holder and subsequently distributing the updated data to each institution [15].

4. Conclusion

This article presents the fundamental developments of artificial intelligence in brain tumor classification, as well as its future prospects and the challenges it faces. The research utilized a literature retrieval method to search for various papers and materials on the Internet, organizing them chronologically and providing brief summaries. After reviewing a significant amount of literature, it can be concluded that artificial intelligence has already achieved remarkable accomplishments in brain tumor classification, with the technology being relatively mature. Moreover, the classification accuracy of current deep learning models has significantly surpassed that of traditional learning models, indicating a rapid advancement in AI models. In the future, it can be hoped that AI can completely detach from human operation, requiring no human intervention, while also simplifying the computational workload as much as possible to enhance the efficiency.

References

[1] Cleveland Clinic. What is a brain tumor? 2022.

[2] Global Cancer Observatory. World Health Organization, 2022.

[3] Johns Hopkins. Brain Tumor Types. 2025.

[4] Joshi DM, Rana NK, Misra VM. Classification of brain cancer using artificial neural network. In: 2010 2nd International Conference on Electronic Computer Technology. IEEE; 2010.

[5] Tandel GS, et al. Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm. Comput Biol Med. 2020; 122: 103804.

[6] Naik J, Patel S. Tumor detection and classification using decision tree in brain MRI. Int J Comput Sci Netw Secur. 2014; 14 (6): 87.

[7] Aggarwal AK. Learning texture features from GLCM for classification of brain tumor MRI images using random forest classifier. Trans Signal Process. 2022; 18: 60 - 63.

[8] Pathak AN, Sunkaria RK. Multiclass brain tumor classification using SVM. Int J Comput Appl. 2014; 97 (23).

[9] Biswas A, Islam MS. Brain tumor types classification using K-means clustering and ANN approach. In: 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST). IEEE; 2021.

[10] Joshi DM, Rana NK, Misra VM. Classification of brain cancer using artificial neural network. In: 2010 2nd International Conference on Electronic Computer Technology. IEEE; 2010.

[11] Agarwal AK, Sharma N, Jain MK. Brain tumor classification using CNN. Adv Appl Math Sci. 2021; 20 (3): 397 - 407.

[12] Sajjad M, et al. multi-grade brain tumor classification using deep CNN with extensive data augmentation. J Comput Sci. 2019; 30: 174 - 182.

[13] Huang NY, Liu CX. Efficient tumor detection and classification model based on ViT in an end-to-end architecture. IEEE Access. 2024; 12: 106096 - 106106.

[14] Wang F, Preininger A. AI in health: state of the art, challenges, and future directions. Yearb Med Inform. 2019; 28 (1): 16 - 26.

[15] Nasr M, et al. Smart healthcare in the age of AI: recent advances, challenges, and future prospects. IEEE Access. 2021; 9: 145248 - 145270.