DOI : https://doi.org/10.56452/7-4-241

ISSN: 0974-5823 Vol. 7 No. 4 April, 2022

International Journal of Mechanical Engineering

COMPARISON OF THE EFFICACY OF DIFFERENT MACHINE LEARNING METHODS USED IN BRAIN TUMOR DETECTION

Ankur Singh Bisht

Associate Professor, Department of Computer Science, Graphic Era Hill University, Dehradun, Uttarakhand India 248002

Abstract

In current era deep learning is applied at every step of life where decision making is involved, whether it is health care, stock exchange, economics, publicity, marketing, sales, communication, robotics, medical imaging, attack detection, security or so on. Deep learning is basically a subset of machine learning.

Deep learning is very widely used to diagnosis the brain tumor by using different imaging techniques i.e. MRI, CT, PET etc. This paper shows review of the research and outcomes of the current techniques and modules used in brain tumor detection by using MRI through deep learning methods, and also compare their efficiency of different approaches of deep learning used in brain tumor detection.

Keyword: Deep learning, health care, MRI, efficiency, machine learning

1. Introduction

A brain tumor is a growth of tissue inside the brain directly influenced by the brain or brain nerves. The physique is classified as malignant or benign. These tumors develop abnormally and put pressure on the brain. These factors may trigger numerous brain diseases. In 2019, it was predicted that approximately 0.7 million individuals in America would be diagnosed with brain tumors. These cases were diagnosed in 0.86 million people. There were 60,800 benign patients and 26,170 malignant patients among these individuals. In the United States, the survival rate of malignant patients is 35% .

Brain tumor with precision Magnetic resonance imaging (MRI) is critical for clinical analysis and assists in making therapy choices for patients [2]. Physical brain tumor categorization from MR pictures with comparable constructions or characteristics is a difficult and time-consuming process contingent on the radiologist's convenience and expertise in correctly recognizing and diagnosing the brain tumor. Mechanized sorting may explain this issue, as it allows for the categorization of brain tumor MR pictures with little human knowledge intervention in the relevant area. With the aid of new and better methods for data analysis, collection, and handing out in computer knowledge, medical pictures show a critical role in detecting brain tumors. These pictures aid in the early identification, mitigation, and treatment of disease's detrimental consequences. The sudden and unexpected expansion of

DOI : https://doi.org/10.56452/7-4-241

brain tissues is referred to as a tumor, and these aberrant cells multiply for unidentified explanations and spread across the brain's local delays and meta-size. Magnetic resonance imaging (MRI) provides information regarding aberrant tissues and the subsequent follow-up (MRI).

Experts examine obtained MRI's to determine the presence of a brain tumor [1, 2]. One of the difficulties we encounter is the identification of tumors using magnetic resonance imaging. Previously, medical professionals carried out tumor identification manually, but this required a significant amount of time, effort, and money on the part of the associated group. Additionally, in physical development, different observers may reach diverse inferences about the presence of the tumor, or even the same viewer may reach a diverse inference at different points in time. Thisis why existing machine learning methods aid practitioners in accurately determining whether an anomaly visible on MRI is a tumor or not [3] [4]. Recognizing the constraints discussed before, we used machine learning to classify brain tumor detection in this work. The procedure begins with feature extraction from the MRI, followed by choosing the required structures and applying classifiers to these structures to increase precision and f-measure. W. P. Rahane et al [28] [29] [30] have worked in the artificial intelligence and machine learning.

2. Related Work

Zacharaki et al. [5] inspected 98 affected persons in 2009 and created a dataset. They began by extracting texture characteristics such as tumor intensity and rotation invariant texture. A binary support vector machine was used to identify high-grade neoplasms from low-grade neoplasms with an accuracy of 85 per cent and 88 per cent, respectively.

In 2015, Manze et al. [6] used various classification methods to the brats 2013 and brats 2012 datasets and merged many of these techniques. All algorithms had an average dice score of 85%.

In 2017, Havaei et al. [7] used the BRATS 2013 (Brain Tumor Segmentation) dataset and a Convolutional Neural Network (CNN) to accelerate the results from 25 seconds to 3 minutes. A Convolutional Neural Network, a maximum of 85 per cent dice score or f-measure, was found (CNN).

In 2018, Zhao et al. [8] used the BRATS information set and deployed a new tumor separation method that combined complete convolutional neural networks (FCNNs) and Conditional Random Fields (CRFs) to produce segmentation outputs with spatial consistency and appearance. When FCCN and CRF were combined with post-handling, the extreme dice score orF-measure of 87 per cent was achieved.

S. Deepak [1] presented a pre-trained deep system architecture, GoogLeNet, in 2019 for the arrangement issue using transfer learning, with an average precision of 98 per cent. Transfer learning enables the usage of a previously qualified CNN prototypical that was created for alternative purposes. Transfer learning has also been shown to have potential in the diagnosis and treatment of medical issues.

Zhou et al. [2] utilized a pre-trained InceptionV3 prototypical to classify benign and malicious kidney tumors on computed tomography (CT) pictures. G. Hemanth et al. [3] presented an approach that included a mean-field span into the CNN's conventional objective purpose. The approach was created and implemented in MATLAB via the usage of image processing.

In contrast to existing algorithms, the suggested CNN performs spontaneously. Through training on huge quantities of data, deep learning demonstrates remarkable performance and

DOI : https://doi.org/10.56452/7-4-241

generalizability. This success is mostly owing to the fast advancement of computing capacity, particularly via graphics processing components, which facilitated the quick creation of sophisticated deep learning processes. Numerous deep learning designs have been created for numerous purposes, with classification in computer vision, voice recognition, and article identification.

Sobhaninia et al. [11] presented a new technique using CNN to categorize the greatest common types of brain tumors, including pituitary, glioma, and meningioma. For tumor segmentation, they used a linkNet network. For training purposes, a total of 2100 pictures were utilized in the network. Approximately 20% of them are verified, while the remainder is utilized for testing. Experimental system testing has revealed that the 0.73 dice score for a single system is reached, while 0.79 is obtained for many systems. Segmentation of tumors in sagittal pictures resulted in this relatively high score. Sagittal scans lack the detail of adjacent organs, and tumors stand out more than in other images. Cui et al. created a novel method for automatically segmenting images founded on a cascaded deep learning convolutional neural network [12]. It includes networks for intra-tumor organization and localization. The MRI tumor section is segmented through tumor localization, and an intra-tumor organization system can delineate the detected tumor range into several sub-regions. The study included the multimodal separation of brain tumors, with 220 instances of high-grade glioma and 54 cases of low-grade glioma included. Positive prognostic value, understanding, and dice coefficients may all be used to do the evaluation.

3. Methodology

The Fig. 1 shows the methodology for determining whether or not a tumor is present in MR images using machine learning methods. After collecting the dataset, it is preprocessed. After preprocessing, favorable characteristics are identified. The dataset is then trained and tested, and the results are compared to determine the most effective method.

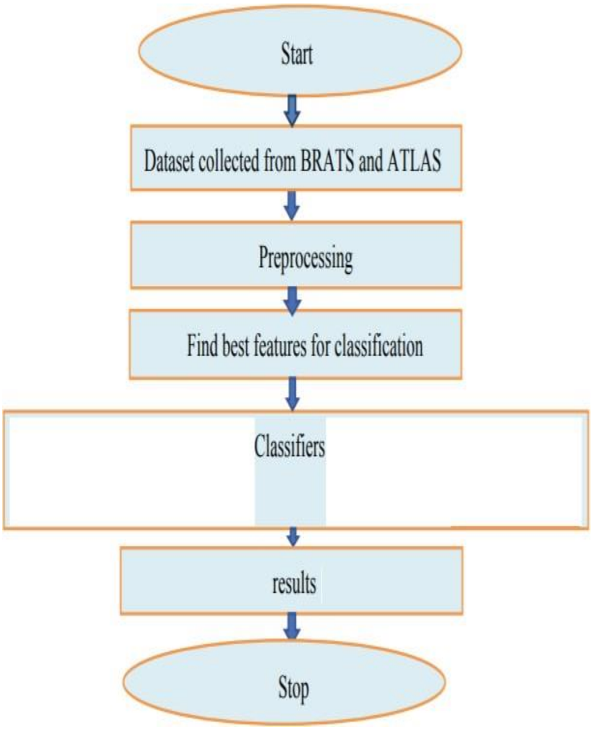

Fig. 1 Flow of tumor detection

DOI : https://doi.org/10.56452/7-4-241

4. Dataset

Two sites provide MR image datasets. BRATS 2015 is the initial source [9]. The collection contains only completely anonymized MR images [6, 10]. The second foundation of the datasetis the Harvard Medical School's whole brain ATLAS, which includes MRIs with and without tumors. Two pictures from the BRATS 2015 dataset are shown in Figure 2, while three images from the entire brain ATLAS dataset are shown in Figure 3.

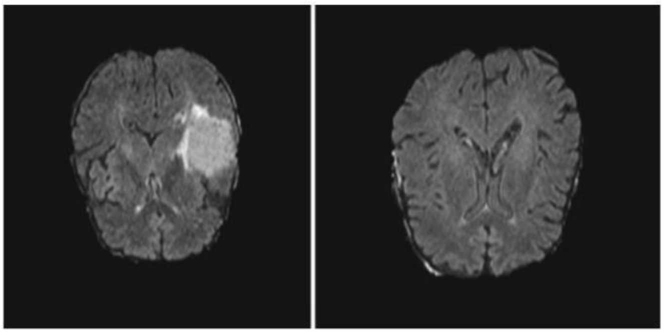

Fig. 2 Image collected from BRATS 2015

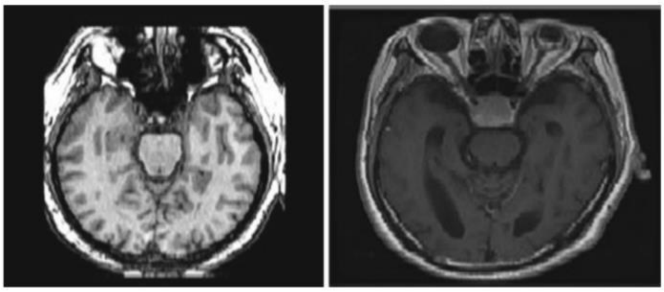

Fig. 3 Image collected from ATLAS

5. Preprocessing of Dataset

The BRATS 2015 dataset was obtained in the. mha format. All MRIs in the. mha format was transformed to the.jpg format for further processing exploitation the free source DIACOM software. Because the ATLAS pictures of the whole brain were previously in.jpg format, they could be downloaded immediately . 885 pictures are utilized in this suggested technique, 488 of which include tumors and 397 of which have normal brain images. Each picture has 54 features, the values of which are saved in.CSV format. Six features are eliminated due to their null values. 48 features are chosen from these 54 features. This is to ensure that the dataset is as clean as possible.

Feature Selection

Accuracy is mostly determined by how machine learning features are chosen. Since having too many characteristics tends to reduce accuracy, it is critical to prioritize just the most useful features. The suggested method employs 48 characteristics, some of which do not add to accuracy and in other cases reduce it, indicating that feature selection is critical for achieving accuracy.

Four feature selection methods are employed in total; the first is univariate feature choice

DOI : https://doi.org/10.56452/7-4-241

[11], commonly recognized as chi-square, which analyzes each feature independently and determines its degree of association with the response variable; this technique employs 37 characteristics. Recursive feature elimination (RFE) is the second technique for selecting features. With random forest, the model is trained, and the features are ranked; the features with the lowest ranking are then removed; in this case, a total of 20 features are utilized. Thirdly, recursive feature removal with cross-validation and random forest classifier (RFECV), comparable to RFE.

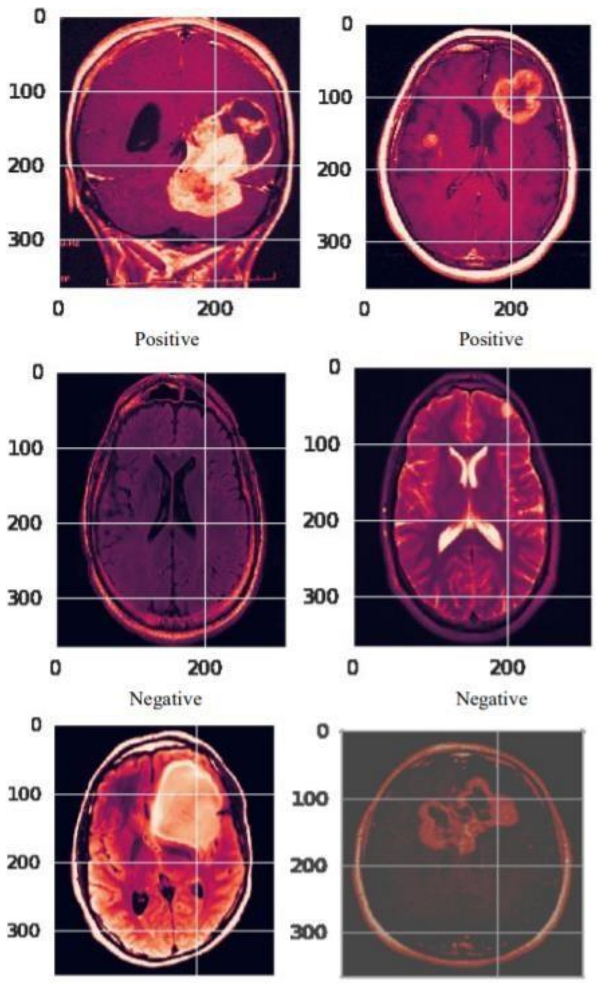

Fig. 4. Test Sample for showing the Level of detection

6. K-Means Algorithm

K-Means is the most often utilized technique since it is based on the centroid idea. The K-Means Clustering Algorithm:

1. The dataset is segregated into K clusters, and information points are arbitrarily allocated to theclusters, resultant in clusters with approximately equal data points.
2. Each information point contains the following: a. Determine the distance between each information point and each cluster. b. Allow the information point to remain in its current location if it is closest to its cluster. If the information point is not nearest to its cluster, it should be moved to the closest cluster.
3. Rep the initial stage until no data point moves from one cluster to another after a full run

through all data points. Clusters are now steady, and the clustering procedure is complete.

4. The preliminary partitioning strategy significantly impacts the end clusters' inter-and intra- cluster distances and cohesiveness [1] [5].

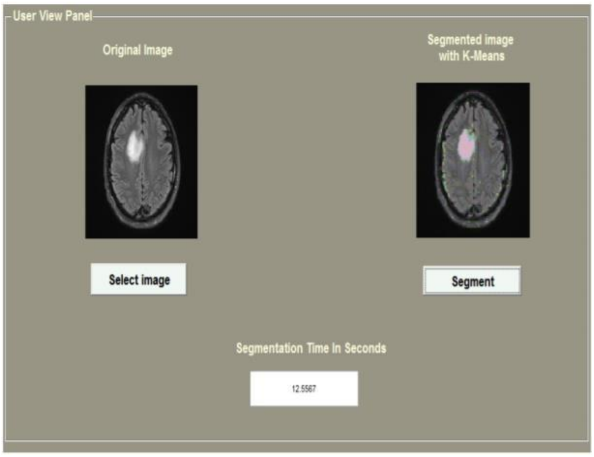

Fig.5: Pre-Processing and K-Means Algorithm output

According to Fig. 5, the K-Means classifier with feature selection provided a high recall.

7. Conclusion

Our findings demonstrate unequivocally that utilizing K-Means classifiers-based feature selection techniques, high precision, recall, specificity, and f1 can be obtained. It is expected thatcombining classifiers with nature-inspired algorithms such as the grey wolf optimizer and cuckoo search would result in increased accuracy in the future.

References

1. Deepak, S., and P. M. Ameer, “Brain tumor classification using deep CNN features via transfer learning”, Computers in biology and medicine 111 (2019): 103345.
2. L. Zhou, Z. Zhang, Y.C. Chen, Z.Y. Zhao, X.D. Yin, H.B. Jiang, “A deep learning-based radionics model for differentiating benign and malignant renal tumors”, Transl, Oncol. 12 (2)(2019) 292–300.
3. Hemanth, G., M. Janardhan, and L. Sujihelen, “Design and Implementing Brain Tumor Detection Using Machine Learning Approach”, In 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), pp. 1289-1294. IEEE, 2019.
4. Smirnov, Evgeny A., Denis M. Timoshenko, and Serge N. Andrianov, “Comparison of regularization methods for imagenet classification with deep convolutional neural networks”,Aasri Procedia 6 (2014): 89-94.
5. Wu, Songtao, Shenghua Zhong, and Yan Liu, “Deep residual learning for image steganalysis”, Multimedia tools and applications 77, no. 9 (2018): 10437-10453.
6. Szegedy, C., S. Ioffe, V. Vanhoucke, and A. Alemi, “Inception-ResNet and the Impact of Residual Connections on Learning”, arXiv preprint arXiv:1602.07261.
7. Bernal, Jose, Kaisar Kushibar, Daniel S. Asfaw, Sergi Valverde, Arnau Oliver, Robert

Martí, and Xavier Lladó, “Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review”, Artificial intelligence in medicine 95 (2019): 64-81.

8. obhaninia, Zahra, Safiyeh Rezaei, Alireza Noroozi, Mehdi Ahmadi, Hamidreza Zarrabi, Nader Karimi, Ali Emami, and Shadrokh Samavi. “Brain tumor segmentation using deep learning by type specific sorting of images”, arXiv preprint arXiv: 1809.07786 (2018).
9. Ostrom, Quinn T., Gino Cioffi, Haley Gittleman, Nirav Patil, Kristin Waite, Carol Kruchko, and Jill S. Barnholtz-Sloan, “CBTRUS statistical report: primary brain and other central nervous system tumors diagnosed in the United States in 2012–2016”, Neurooncology 21, no. Supplement_5 (2019): v1-v100.
10. Gordillo N, Montseny E, Sobrevilla P (2013), “State of the art survey on MRI brain tumor segmentation”, Magn Reson Imaging 31(8):1426–1438
11. Clark MC, Hall LO, Goldgof DB, Velthuizen R, Murtagh FR, Silbiger MS (1998), “Automatic tumor segmentation using knowledge-based techniques”, IEEE Trans Med Imaging 17(2):187– 201.