IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 5, May 2022

DOI: 10.17148/IJARCCE.2022.115203

Brain Tumor Detection

Syed Amaanullah[1], Pallavi N[2]

[1,2] Atria Institute of Technology, Visvesvaraya Technological University, India

Abstract: One of the most difficult challenges in medical image processing is detecting brain tumours. The challenge is challenging to complete since the photographs have a lot of variety, as brain tumours exist in a variety of shapes and textures. Brain tumours are made up of several types of cells, and the cells can reveal information about the tumor's nature, severity, and rarity. Tumors can appear in a variety of areas, and the location of a tumour can reveal information about the sort of cells that are creating it, which can help with further diagnosis. The process of detecting brain tumours can be made more difficult by issues that can be found in practically all digital images, such as lighting issues. The picture intensities of tumour and non-tumor images can overlap, making it challenging for any model to make accurate predictions from raw images. This research offers a novel method for detecting brain cancers from various brain pictures by using image preprocessing techniques such as histogram equalisation and opening, followed by a convolutional neural network. Apart from the picture preprocessing approaches that have been finalised for training, the study also explores the impact of alternative image preprocessing techniques on our dataset. The experiment was done out on a dataset that included tumours of various shapes, sizes, textures, and locations. For the classification challenge, a Convolutional Neural Network (CNN) was used. CNN achieved a recall of 98.55 percent on the training set and 99.73 percent on the validation set in our research, which is quite impressive.

Keywords: Brain Tumor Detection, Convolutional Neural Networks, Deep Learning, Image Processing, Computer Vision, Computer-aided Diagnosis, Transfer Learning.

I. INTRODUCTION

A brain tumour is a mass of tissue in which cells multiply at an uncontrollable rate. It comes from a variety of cells, both inside and outside the brain. Primary tumours are those that begin in the brain and spread to other areas of the body, whereas secondary tumours are those that spread to other parts of the body. Tumors can have a variety of sources, depending on the cells or origins obtained from various types of tumours. Gangliogliomas, for example, are tumours that contain neoplastic neurons and are typically grade I or low-grade tumours, indicating that the tumour is well-differentiated and grows slowly. Meningioma, which arises from the meninges, is another example. It can be treated with radiotherapy, tomotherapy, and surgery (craniotomy). Although brain tumours are relatively uncommon, with about 1.4 percent of new occurrences each year, mortality from brain tumours have grown in developed countries during the last few decades. CNS tumours account for 2% of malignancies in India, with rates ranging from 5 to 10 per 100,000 population on the rise.

Computer-assisted disease diagnosis has gained popularity in recent years, and it is assisting clinicians in making quick decisions. One strategy is to use Convolutional Neural Networks (CNN) to learn the spatial and temporal properties required to detect the disease from a given dataset. A Convolutional Neural Network is a form of neural network that is specifically designed to handle picture datasets. The basic premise of this neural network is to extract features by performing a convolution operation between the kernel and the image. The weights matrix is iteratively updated in all neural networks to learn. The optimal kernel values for all layers of the CNN model must be found here. As a result, the kernel values serve as the model's weights, and the optimal kernel values are gradually acquired by backpropagation and gradient descent. The backward computation of derivatives of the loss function with regard to weights and biases is known as backpropagation. Gradient descent is the process of updating the weights on a regular basis so that the loss or error decreases with each iteration. A convolutional layer is frequently combined with a pooling layer, and numerous such convolutional layer-pooling layer pairings can be connected. For the final learning process, we can have a few Dense layers and dropout layers. Dropout layers are used to solve the problem of overfitting. The classification duty is done by the last output layer, which might have only one neuron for a binary classification task or more than one for a multi-class classification task. Capsule networks, a type of neural network that can encode spatial information as well as the probability of an object appearing in a picture, are gaining popularity and have been employed in several recent publications.

Abnormal blobs in the brain in MRI scans (or any other scan) identify brain cancers. These blobs or areas are illuminated differently than the rest of the brain. They're frequently brighter than the rest of the room. The procedure of segmenting tumours in MRI images is a time-consuming one. We segmented the tumour based on features like illumination. The appearance of tumours in MRI pictures is significant since it suggests the existence of cancer.

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁒ Impact Factor 7.39 ⁒ Vol. 11, Issue 5, May 2022

DOI: 10.17148/IJARCCE.2022.115203

In this study, we offer a new approach for detecting brain tumours in MRI scans. To improve our dataset, we started with image preprocessing, which included morphological approaches and histogram equalisation. After that, the Convolutional Neural Network is used to classify tumour and non-tumor images (CNN). This work emphasises the need of image processing because digital images have a variety of issues, such as the illumination problem mentioned earlier, and without suitable image preprocessing approaches, CNNs might be misled into learning inaccurate features and producing incorrect outputs.

II. LITERATURE SURVEY

Research work by 9 different authors has been discussed on the basis of varied deep learning techniques and architectures adopted by them.
Sakshi Ahuja et al.,[1] used transfer learning and superpixel technique for detection of brain tumor and brain segmentation respectively. The dataset used was from BRATS 2019 brain tumor segmentation challenge and this model was trained on the VGG 19 transfer learning model. Using the superpixel technique the tumor was divided between LGG and HGG images. This resulted in an average of dice index of 0.934 in opposition to ground truth data.

Hajar Cherguif et al.,[2] used U-Net for the semantic segmentation of medical images. To develop a good convoluted 2D segmentation network, U-Net architecture was used. BRATS 2017 dataset was used for testing and evaluating the model proposed. The U-Net architecture proposed had 27 convolutional layers, 4 deconvolutional layers, Dice_coef of 0.81.

Chirodip Lodh Choudhury et al.,[3] made the use of deep learning techniques involving deep neural networks and also incorporated it with a Convolutional Neural Network model to get the accurate results of MRI scans. A 3-layer CNN architecture was proposed which was further connected to a fully Connected Neural Network. F-score equal to 97.33 and an accuracy equal to 96.05% was achieved.

Ahmad Habbie et al.,[4] MRI T1 weighted images were taken and using semi automatic segmentation analyzed the possibility of a brain tumour using an active contour model. The performance of morphological active contour without edge, snake active contour and morphological geodesic active contour was analyzed. MGAC performed the best among all three as suggested by the data.

Neelum et al.,[5] used a concatenation approach for the deep learning model in this paper and the possibility of having a brain tumor was analyzed. Pre trained deep learning models which are Inception - v3 and DenseNet201 were used to detect and classify brain tumors. Inception - v3 model was pre trained to extract the features and these features were concatenated for tumor classification. Then, the classification part was done by a softmax classifier.

Ms. Swati Jayade et al.,[6] used Hybrid Classifiers. The classification of tumors was done into types, malignant and benign. Feature dataset here was prepared by Gray level Co- occurrence Matrix (GLCM) feature extraction method. A hybrid method of classifiers involving KNN and SVM classifiers was proposed to increase efficiency.

Zheshu Jia et al.,[7] the author made a fully automatic heterogeneous segmentation in which SVM (Support Vector Machine) was used. For training and checking the accuracy of tumor detection in MRI images, a classification known as probabilistic neural network classification sytem had been used. Multi spectral brain dataset is used and this model focused on the automated segmentation of meningioma.

DR. Akey Sungheetha, DR. Rajesh Sharma R.[8] used Gabor transform along with the soft and hard clustering for detecting the edges in the CT and MRI images. A total of 4500 and 3000 instances of MRI images and CT were used respectively. K-means clustering was used for the separation of similar features into sub-groups To represent the images in the form of histogram properties, the author used Fuzzy c means.

Parnian Afshar et al.,[9] used a bayesian approach for the classification of brain tumor using capsule networks. To improve the results of tumor detection, capsule network instead of CNN was used as CNN can loose the important spatial information. The team proposed BayesCap framework. To test the proposed model they used a benchmark brain tumor dataset.

III. CONVOLUTION NEURAL NETWORK

The visual cortex inspires the connectivity between the layers of a convolutional neural network, which is a sort of feed forward artificial neural network. CNNs (Convolutional Neural Networks) are a type of deep neural network used to

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁘ Impact Factor 7.39 ⁘ Vol. 11, Issue 5, May 2022

DOI: 10.17148/IJARCCE.2022.115203

analyse visual information. They're used in image and video recognition, picture classification, and natural language processing, among other things. Convolution is the initial layer that extracts characteristics from an input image. Convolution preserves the link between pixels by learning visual qualities with small squares of input data. It's a mathematical process with two inputs: an image matrix and a filter or kernel. To build output feature maps, each input image will be sent through a succession of convolution layers with filters (kernels). Here's how CNN works in detail.

Convolutional neural networks are made up of four layers: convolutional layers, ReLU layers, pooling layers, and fully connected layers.

Convolutional Layer

After the computer reads an image in the form of pixels, convolution layers are used to create a tiny patch of the image. The characteristics or filters refer to these photos or patches. Convolutional layer gets a lot better at spotting similarities than complete image matching scenes by transmitting these rough feature matches in nearly the same position in the two images. These filters are compared to the fresh input photos, and if they match, the image is appropriately categorised. Line up the features and the image, then multiply each image, pixel by pixel, add the pixels, then divide the total number of pixels in the feature. We make a map and place the filter's values in the appropriate locations. Similarly, we'll move the feature to every other location in the image to see how it matches that area. Finally, as an output, we will get a matrix.

ReLU Layer

The rectified linear unit (ReLU) layer removes any negative values from filtered images and replaces them with zero in this layer. This is done to prevent the values from accumulating to zero. This is a transform function that only activates a node if the input value is more than a particular number; if the input is less than zero, the output will be zero, and all negative values will be removed from the matrix.

Pooling Layer

We minimise or shrink the image size in this layer. We start by choosing a window size, then specifying the appropriate stride, and finally walking your window through your filtered photographs. Then take the maximum values from each window. This will combine the layers and reduce the image's and matrix's size. The fully linked layer receives the decreased size matrix as input.

Fully Connected Layer

We need to stack up all the layers after passing it through the convolutional layer, ReLU layer and the pooling layer. The fully connected layer used for the classification of the input image. These layers need to be repeated if needed unless you get a 2x2 matrix. Then at the end the fully connected layer is used where the actual classification happens.

The flowchart for Data Acquisition

The flowchart for data collection is shown in Figure 1.1. A thorough analysis is carried out when the data set is acquired from a source. Only if the image meets our requirements and is not duplicated is it chosen for training/testing purposes.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁑ Impact Factor 7.39 ⁑ Vol. 11, Issue 5, May 2022
DOI: 10.17148/IJARCCE.2022.115203

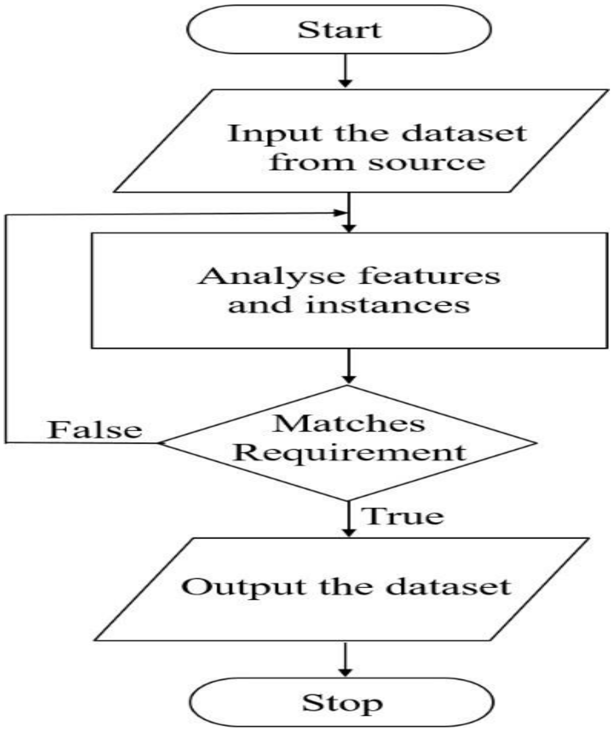

Figure 1.1 Flowchart for data acquisition

IMAGE PRE - PROCESSING

1. Global Thresholding
This strategy was shown to be useless. The reason for this is that various photographs have varied levels of lighting, i.e. different pixel intensities. Because of the varying pixel intensities in the photos, a global threshold cannot be established for all of them. The tumour appears brighter than the rest of the brain area in the tumour photos. When we use a threshold value to differentiate the bright tumour region from the darker brain portion, it causes problems in some non-tumor photos when the entire brain portion is bright. Setting a threshold will cause these non-tumor photos to be classified as tumour images, proving futile.

2. Adaptive Thresholding
Adaptive thresholding does not use a single set threshold value over the whole image. Instead, the threshold is determined by the range of intensities in the pixel's immediate vicinity. As a result, the threshold values for different sections of the image will differ. As a result, dynamic thresholding for distinct photos is possible. The contours are highlighted in the adaptive thresholding output, as can be seen. The problem is that the outlines are nearly as plentiful in the tumour area as they are in non-tumor areas. This makes distinguishing the tumour from the rest of the brain challenging.

3. **Sobel filter**
A pair of convolutional kernels make up the Sobel filter, which is an edge detection filter. The first of the two identifies edges that run vertically, while the other detects edges that run horizontally.

4. **High Pass filter**
The photos are subjected to a 3x3 high pass filter kernel with an 8 in the centre and a -1 everywhere else. Because it's a derivative filter, it emphasises the edges while darkening the background. It performs the same thing here, and as a result, the tumour becomes indistinguishable from the background, which is a terrible outcome. As a result, we are unable to apply this strategy to our work..

5. **Median Blur**
When it comes to reducing Salt & Pepper noise, the median filter is extremely successful. It accomplishes this by substituting the centre values of the image's window with the median of all the values in that window. The pixel intensities of the salt and pepper noise pixels are on the extreme ends of the list of pixel intensities (arranged in ascending order for

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 5, May 2022
DOI: 10.17148/IJARCCE.2022.115203

median computation) of a window, i.e. around 0 for black and around 255 for white in an 8-bit image, so they lie on the extreme ends of the list of pixel intensities (arranged in ascending order for median computation). As a result, they rarely become the median, and non-noise pixels become the centre value, thus eliminating noise pixels. The edges and borders are kept in this case. In this situation, there isn't much of a difference between the original and preprocessed image. As a result, it is ineffective.

6. **Histogram Equilization**

Overall, this preprocessing procedure improves the situation. This is due to the fact that histogram equalisation normalises pixel intensities, therefore normalising some of the lighting issues. Although the image is non-tumor, the whiter area on the top left part of the brain appears to be a tumour, despite the fact that it is not. The visual difference between that area and the rest of the brain was decreased via histogram equalisation. This is a promising result, and we can now move forward with fitting a Convolutional Neural Network (CNN) model to histogram equalised photos.

7. **Dilation**

Dilation is an image preprocessing technique that enlarges the edges of objects by adding pixels. Due to the inclusion of white pixels on the boundaries, white regions such as tumours grow in size following dilation, and the gaps in the white regions are filled as well. If we convolve on our image with a 3x3 structuring element containing all 1s, any background pixel that is surrounding by at least 1 white pixel will be transformed to foreground pixel. As a result, there is a decrease in darker areas and an increase in lighter areas, highlighting the tumour more. This technique appears to be promising, and we will use it to process images as well.

8. Erosion

Erosion is the polar opposite of dilation in that it removes pixels from the object's edges. After erosion, white regions such as tumours reduce in size, while gaps and holes in the white regions grow in size. If we convolve on our image with a 3x3 structuring element containing all 1s, any foreground pixel that isn't surrounded by white pixels will be transformed to background pixel. This may lead to the tumours (the primary subject of our research) being overlooked..

IV. CONCLUSION

Brain tumours, particularly malignant ones, are thought to be nearly incurable and fatal. The necessity for early detection stems from the fact that brain tumours can present with symptoms that aren't immediately frightening. The most typical sign of a brain disease is a headache, which, in the case of brain tumours, increases over time. As a result, there have been numerous situations where the fatality rate from a brain tumour has increased as a result of delayed diagnosis. Brain tumor diagnosis begins with an MRI scan which is followed by studying a tissue sample for determining the type of tumor. MRI scan can also reveal additional details such as the size of the brain tumor.

This research provides a novel strategy for picture manipulation involving image processing techniques that will help our CNN model better distinguish tumour and non-tumor images. Using image processing techniques, we were able to resolve the lighting difficulties and bring the tumour into focus. Data augmentation can be used to lessen the likelihood of overfitting by artificially increasing the size of a training dataset, resulting in improved performance and the model's capacity to generalise. As a pre-trained model, transfer learning can be applied..

REFERENCES

[1] Jakesh Bohaju, (2020, July). Brain Tumor, Version 3. Retrieved September 22, 2020, from https://www.kaggle.com/jakeshbohaju/brain-tumor.
[2] Navoneel Chakrabarty, (2019, April). Brain MRI Images for Brain Tumor Detection, Version 1. Retrieved September 18, 2020, from https://www.kaggle.com/navoneel/brain-mri-images-for-brain
[3] Sartaj, (2020, May). Brain Tumor Classification (MRI), Version 2.
[4] Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, Har Pal Thethi, "Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM", International Journal of Biomedical Imaging, vol. 2017, Article ID 9749108, 12 pages, 2017. https://doi.org/10.1155/2017/9749108.
[5] Arakeri, M.P., Ram Mohana Reddy, G. An intelligent content-based image retrieval system for clinical decision support in brain tumor diagnosis. Int J Multimed Info Retr 2, 175–188 (2013). https://doi.org/10.1007/s13735-013-0037-5
[6] Sachdeva J, Kumar V, Gupta I, Khandelwal N, Ahuja CK. Segmentation, feature extraction, and multiclass brain tumor classification. Journal of Digital Imaging. 2013 Dec;26(6):1141-1150. DOI: 10.1007/s10278-013-9600-0.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⋇ Impact Factor 7.39 ⋇ Vol. 11, Issue 5, May 2022

DOI: 10.17148/IJARCCE.2022.115203

[7] D. Sridhar and I. Murali Krishna, "Brain Tumor Classification using Discrete Cosine Transform and Probabilistic Neural Network," 2013 International Conference on Signal Processing, Image Processing & Pattern Recognition, Coimbatore, 2013, pp. 92-96, doi: 10.1109/ICSIPR.2013.6497966.

[8] Padma Nanthagopal, A., Sukanesh Rajamony, R. Automatic classification of brain computed tomography images using waveletbased statistical texture features. J Vis 15, 363–372 (2012). https://doi.org/10.1007/s12650-012-0140-3.

[9] Mariam Saii, Zaid Kraitem, Automatic Brain Tumor Detection in MRI Using Image Processing Techniques, Biomedical Statistics and Informatics. Vol. 2, No. 2, 2017, pp. 73-76. doi:10.11648/j.bsi.20170202.16.

[10] L. Guo, L. Zhao, Y. Wu, Y. Li, G. Xu and Q. Yan, "Tumor Detection in MR Images Using One-Class Immune Feature Weighted SVMs," in IEEE Transactions on Magnetics, vol. 47, no. 10, pp. 3849-3852, Oct. 2011, doi: 10.1109/TMAG.2011.2158520.

[11] Nair M, Varghese C, Swaminathan R. Cancer: Current Scenario, Intervention Strategies and Projections for 2015. NCMH Background Papers; 2015. [Google Scholar] [Ref list]

[12] Yeole BB. Trends in the brain cancer incidence in India. Asian Pac J Cancer Prev. 2008;9:267–70.[PubMed][Google Scholar]

[13] Dasgupta, Archya et al. “Indian data on central nervous tumors: A summary of published work.” South Asian journal of cancer vol. 5,3 (2016): 147-53. doi:10.4103/2278-330X.187589.

[14] Papadopoulos MC, Saadoun S, Binder DK, Manley GT, Krishna S, Verkman AS. Molecular mechanisms of brain tumor edema. Neuroscience. 2004;129(4):1011-20. doi: 10.1016/j.neuroscience.2004.05.044. PMID: 15561416.

[15] Niklas Donges (2019, June 16). What is transfer learning? Exploring the popular deep learning approach. Builtin. https://builtin.com/datascience/transfer-learning.

[16] American Association of Neurological Surgeons. (n.d.). “Classification of Brain Tumors”. https://www.aans.org/en/Media/Classifications-ofBrain-Tumors

[17] Charles Patrick Davis. (2020, August 24). “How do you get Brain Cancer?” https://www.medicinenet.com/brain_cancer/article.htm

[18] Vijayakumar, T. "Classification of Brain Cancer Type Using Machine Learning." Journal of Artificial Intelligence 1, no. 02 (2019): 105-113.

[19] Pandian, A. Pasumpon. "Identification and classification of cancer cells using capsule network with pathological images." Journal of Artificial Intelligence 1, no. 01 (2019): 37-44.