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Article Title: A Deep Learning Method for Detecting Brain Tumour in MRI Images

A Deep Learning Method for Detecting Brain Tumour in MRI Images

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ABSTRACT

Brain tumour are the primary cause of cancer-related mortality. Brain tumour treatment and early detection are important. The tumour is not very big. A deep learning method is put forth in this paper for the segmentation of brain tumour in MRI data. An image is first pre-processed using a median filter. Spatial processing is carried out by a median filter to minimise noise in an image. This filter evaluates how each pixel in the image contrasts with the pixels around it. GLCM employs the feature extraction technique. For the purpose of obtaining statistical skin parameters in a specific direction and distance, Gray Level Co-Occurrence Matrix (GLCM) approach is used. A technique for estimating solutions to mathematical maximisation and minimization problems that are extremely challenging or unattainable is called particle swarm optimisation (PSO). This paper use the convolutional neural network (CNN) technique. An early diagnosis of diabetic retinopathy has been made easier by the use of CNN algorithms. This paper is implemented using Matlab software.

Keywords: Brain tumors, Median filter, convolutional neural network (CNN), Gray Level Co-ocurrence Matrix (GLCM), Particle swarm optimization (PSO),

1 Introduction

Brain tumour detected with magnetic resonance imaging (MRI) play a key role in the diagnosis of such conditions. Deep learning (DL), a kind of AI, has transformed new techniques for automated medical image diagnosis [1]. By using a combination of machine learning techniques to classify brain abnormalities (tumour and strokes) in MRI images. The texture features are extracted with the help of a mysterious directional based quantized extrema pattern. [2]. The sizes of brain tumour vary, and they are frequently hard to find. It may be impossible to precisely gauge a brain tumour's size and resolution in its early stages, making detection much more challenging. [3]. For better diagnosis, growth rate forecasting, and treatment planning, data sets are crucial. However, because to the severe partial volume impact, significant heterogeneity in tumour shapes, and imaging conditions, particularly for gliomas, automating this process is difficult [4]. A correct identification of a brain tumour can be crucial for initiating the right treatment, which eventually lowers the patient survival percentage. For the detection of brain tumour from 2D Magnetic Resonance (MR) images, a deep learning-based classification technique has recently gained popularity [5]. However, more work needs to be done to more accurately categorise these multiple class malignant tumour into their respective classes [6]. The use of computer assisted methods is necessary to get over these restrictions. The numerous traditional and hybrid machine learning models were created and carefully analysed to categorise the photos of brain tumour without the use of any human involvement [7]. An innovative deep learning based technique for GBM patients' OS prediction that can extract tumour genotype-related variables from brain data and include them into OS prediction [8]. For accurate and speedy training, images from the dataset were originally enhanced, cropped, and pre-processed. A deep transfer learning model is trained and evaluated using three alternative optimisation strategies [9]. An efficient brain tumour segmentation method built on the foundation of deep learning techniques employs conditional Radom Fields (CRF) and heterogeneous convolution neural networks (HCNN) to generate appearance and spatial accuracy results [10].

An automated tumour categorization system is crucial for assisting radiologists and physicians in detection of brain tumour. An accuracy of the present techniques has to be improved for effective treatments. In this paper, a deep learning technique is proposed for the segmentation of brain tumour in MRI scans. The list below demonstrates how the paper is organised: Section II describes the most recent work. Section III describes the proposed work in detail. The results are presented in Section IV. Section V provides a conclusion.

2 Recent Works

Gunasekaran Manogaran et al (2018) [11] have suggested the application of artificial intelligence to magnetic resonance imaging, which has been used in a number of clinical trials. An automatic analysis of brain cancers is acknowledged as a vital area of research because a returned brain images must be enhanced using a segmentation method that is particularly resistant to noise and cluster size sensitivity concerns. An analytical method is used to determine an algorithm's mean error rate.

Mohamed Shakeel et al (2019) [12] have outlined an image processing in early detection of diseases including breast, lung, and brain tumour in order to provide the proper treatment. Pathologists are troubled by this technique for classifying brain tumour that uses MLBPNNs (machine learning-based back propagation neural networks). This imaging sensor includes a

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imaging sensor that is intended to transmit tumour warmth data to a specialised clinician for patient wellbeing screening and for control of ultrasound measurement level, particularly when there should be a scenario comprising elderly patients in remote areas.

Abdu Gumaei et al (2019) [13] have proposed a critical action that is dependent on the medical professional's expertise and understanding. An accurate brain tumour classification system using a hybrid feature extraction technique and a regularised extreme learning machine (RELM). The method begins by applying a min-max normalisation procedure to pre-process the brain images in order to improve contrast of brain's edges and regions. A series of tests are run on a brand new, publicly available dataset of brain scans in order to assess and contrast the proposed approach.

Neelum Noreen et al (2020) [14] have described the fatal illness, and radiologists' work of classifying it is difficult due to the heterogeneous makeup of the tumour cells. The diagnosis of brain tumour using magnetic resonance imaging (MRI) has recently been promised by computer-aided diagnosis-based techniques. Recent uses of pre-trained models typically extract features from bottom layers that differ between natural and medical images. A process of multilevel feature extraction and concatenation for brain tumour early diagnosis. The three-class brain tumour dataset that was used to examine both scenarios was required for public use.

Andres Anaya-Isaza et al (2022) [15] have argued that the rapid development of deep learning networks has made it possible to complete difficult tasks, including those in the intricate field of medicine. An impact of several traditional data augmentation methods on ResNet50 network's ability to detect brain tumour. But in order for these networks to be extremely generalizable and perform at a high level, a big corpus of data must be used. As a result of the difficulty in obtaining data, data augmentation techniques are commonly employed to train networks using tiny data sets. They are especially important in the field of medicine.

3 Proposed Work Explanation

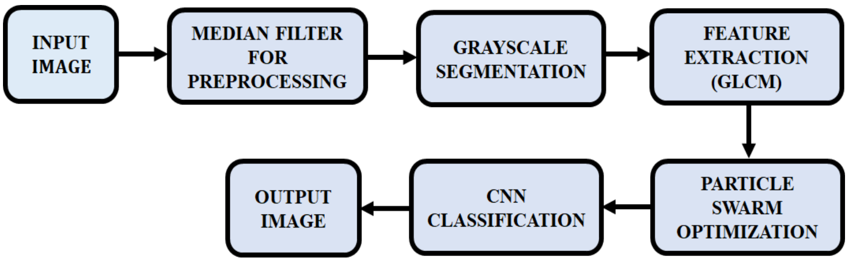

Figure 1: *Block Diagram for Proposed System*

The proposed approach employs deep learning to segment brain tumour via MRI images. An input image is pre-processed using the median filter. To reduce noise in an image, spatial image processing is done using a median filter. The Grayscale segmentation block obtains this dataset after pre-processing. The feature extraction stage comes next, and it is accomplished using

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GLCM. For the purpose of retrieving statistical skin parameters in a specific direction and distance, the Grey Level Co-Occurrence Matrix (GLCM) approach is used. Particle swarm optimisation is the next stage, a method for approximating answers to extremely challenging or impractical numerical maximisation and minimization issues. The accuracy is then improved by using the CNN classification method. To achieve the desired result overall.

3.1 Pre-processing

The goal of pre-processing, which involves making geometric alterations to images, is to improve the image data by minimising undesired distortions or enhancing particular parts of an image that are essential for subsequent processing.

3.2 Median Filter

An image or signal's noise can be reduced using the median filter, a non-linear digital filtering technique. A common pre-processing technique to enhance an outcomes of subsequent processing, like edge identification on an image, is noise reduction.

3.3 Image Segmentation

In addition to searching for patterns of similarity within an image's regions, a common strategy is to search for impulsive changes in pixel values, which frequently indicate the edges defining a region. This approach is used by some approaches, such as region expanding, clustering, and thresholding.

3.4 Gray Scale Segmentation

According to their positions and grey values, the suggested image segmentation approach converts each pixel in the medical grayscale image to 3D coordinates as the pixel features point cloud.

3.5 Feature Extraction

The term "feature extraction" refers to a process used to extract visual data from images for indexing and retrieval. Examples of general low level or minimal image properties include the extraction of colour, texture, and shape. It is also possible to include domain specific features.

3.6 Gray Level Co - Ocurrence Matrix

A statistical method for evaluating texture that considers spatial relationship between pixels is known as gray level co-occurrence matrix (GLCM). The second order statistical texture analysis method is called GLCM.

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3.7 Particle Swarm Optimization

By constantly attempting to improve the quality of a proposed solution, particle swarm optimisation (PSO) is a computational technique for problem optimisation. It solves issues by moving a population of potential solutions called particles, through search space in accordance with a simple mathematical formula over the particle's position and velocity.

3.8 Convolutional Neural Networks

In recent years, the fields of semantic segmentation and radar imaging have seen significant advancements in convolutional neural networks (CNNs). In-depth learning methods like CNNs were developed specifically for image recognition and classification. A multitude of real-world applications have made use of CNN. This network was developed and is similar to multi-layered neural networks. The biological neural networks utilised in speech recognition, image processing, and other applications are the same as CNNs. Instead of manually analysing the MRI images, a CNN-based algorithm will assist medical practitioners in their therapeutic role and accelerate the healing process. Examples of CNN include face recognition, image categorization, and other computer vision applications. It is similar to the basic neural network. CNNs also have learnable parameters, including weights and biases, like neural networks do. Despite their complexity in terms of resources and expertise, CNNs offer in-depth conclusions.

3.8.1 Classification of CNN

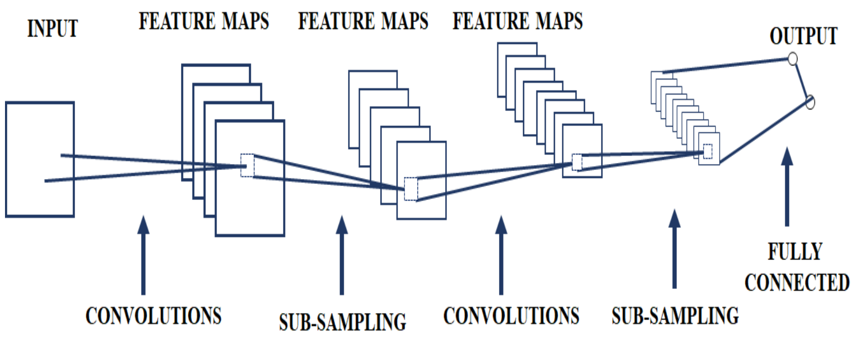

Figure 2: *CNN architecture diagram*

There are several CNN layers, as depicted in the CNN architecture diagram in figure 2. Convolutional Layer, Pooling, and Fully Connected (FC) Layers are the three types of layers that comprise CNN.

- To extract the numerous features from the input photos, Convolution layer is used. There is a mathematical operation between an input image and a filter of size MxM.
- A pooling layer frequently comes after a convolutional layer. This layer's main goal is to scale down the convolved feature map to save on computing expenses.

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- The weights and biases are comprised in Fully Connected (FC) layer, which connects the neurons between two layers. A CNN Architecture's final few layers are frequently positioned before the output layer.

4 Results and Discussion

4.1 Input image

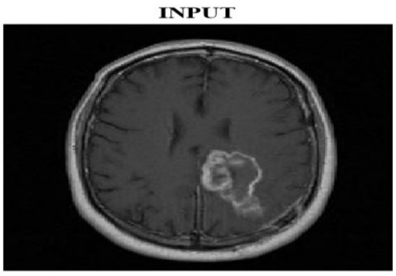

Figure 3: *Input Image*

An input images of the brain are displayed in Figure 3. The input image is also in grayscale. Images of both typical and atypical brain tumour can be found in the database. A single image from those is used as the input.

4.2 Pre-Processing Image

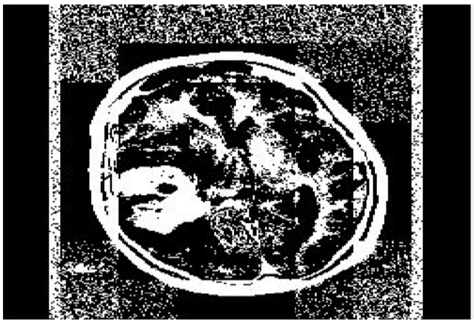

Figure 4: *Pre-processed Image for Median Filter*

Figure 4 shows the median filter for brain images. Before executing the real technique to make an image suitable for further processing, every image needs to go through a minimum amount of pre-processing.

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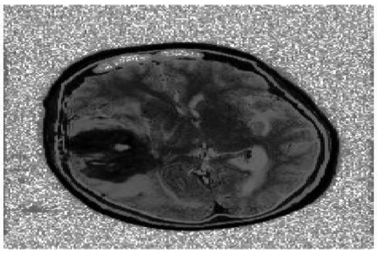
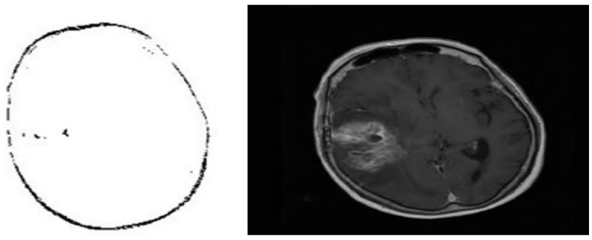


Figure 5: *HIST Analysis*

This filter eliminates noise and undesired distortion from the image to simplify subsequent steps. The image is scaled down to 256*256 pixels during pre-processing. It is a technique used to improve an image's accuracy and accessibility.



(a) **(b)**

Figure 6: *(a) Outline Filter (b) Filtered image*

A line around an element is called an outline. It appears all the way around the element's margin. It differs from the boundary property, though. The element's width and height attributes do not include the width of the outline since the outline is not a component of the element's dimensions. The outline filter and the filtered image are shown in Figures 6(a) and (b) respectively.

4.3 Segmented Image

Figure 7: *The brain image for segmentation*

The grayscale images are converted into binary data. To mask the tumour and non-tumor areas, the image segmentation is used.

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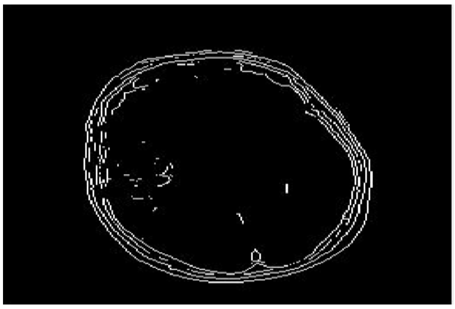

Figure 8: *Edge Detection*

Figure 8 illustrates edge detection. An image processing technique called edge detection is used to find regions in a digital image that have abrupt brightness changes, or, to put it another way, discontinuities. An areas where the brightness of the image varies noticeably are known as the borders of the image.

4.4 Classification

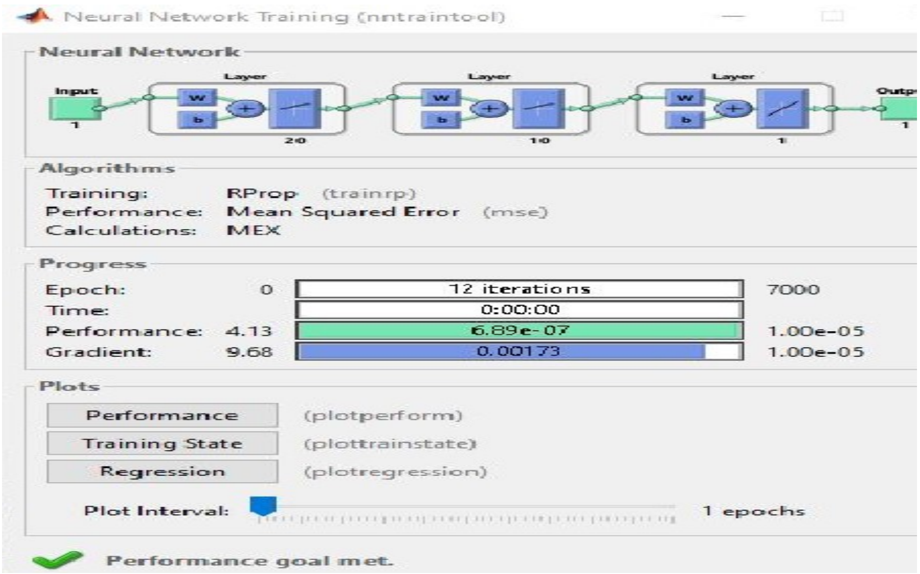

Figure 9: *Classifier-CNN*

The training and testing phases of the CNN-based categorization are separated. The pre-trained neural network receives the test image, and after classifying the test image as a reference, CNN classifies the input image. The CNN classifier's accuracy report is presented in Figure 9.

4.5 Predicted Output

Figure 10 show the output images of the tumour and the non-tumor. The proposed approach provides a clear classification of different tumour types including brain tumour.

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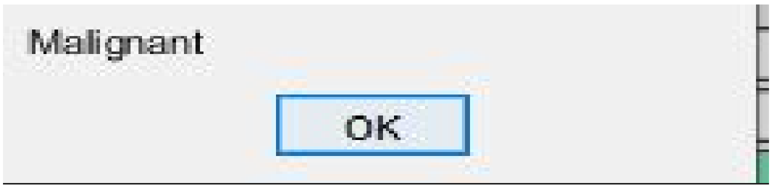

Figure 10: *Predicted Output*

5 Conclusion

Magnetic resonance imaging (MRI)-based early categorization of brain tumour is crucial for the diagnosis of these conditions. To find brain tumour, numerous different imaging diagnostic techniques are performed. Due of its superior picture quality, MRI is frequently employed for these purposes. In this paper a CNN model for brain tumour segmentation from MR images by using deep learning. This highlights efficacy of the suggested approach and possibility of deep learning for MRI-based rapid brain tumour diagnosis. The suggested method outperforms existing models and has good accuracy. The medical community will gain a lot from this endeavour. Future work can still improve the system's performance by utilising bigger data sets and more deep learning approaches for generative adversarial networks (GAN).

Reference

1. Sohaib Asif; Wenhui Yi; Qurrat Ul Ain; Jin Hou; Tao Yi; Jinhai Si, Year: 2022, “Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images”, IEEE Access, Vol: 10, pp. 34716-34730.

2. B.Deepa; M.Murugappan; M.G.Sumithra; Mufti Mahmud; Mabrook S. Al-Rakhami, Year: 2022, “Pattern Descriptors Orientation and MAP Firefly Algorithm Based Brain Pathology Classification Using Hybridized Machine Learning Algorithm”, IEEE Access, Vol: 10, pp. 3848-3863.

3. Hasan Ucuzal; Seyma Yasar; Cemil Colak, Year: 2019, “Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface”, IEEE Access, pp. 01-05.

4. Chao Ma; Gongning Luo; Kuanquan Wang, Year: 2018, “Concatenated and Connected Random Forests With Multiscale Patch Driven Active Contour Model for Automated Brain Tumor Segmentation of MR Images”, IEEE Transactions On Medical Imaging, Vol: 37, no: 8, pp. 1943-1954.

5. Saif Ahmad; Pallab K. Choudhury, Year: 2022, “On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images”, IEEE Access, Vol: 10, pp. 59099-59114.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(04), April 2023, pp. 11-20

6. Ankit Vidyarthi; Ruchi Agarwal; Deepak Gupta; Rahul Sharma; Dirk Draheim; Prayag Tiwari, Year: 2022, "Machine Learning Assisted Methodology for Multiclass Classification of Malignant Brain Tumour", IEEE Access, Vol: 10, pp. 50624-50640.

7. Mohammad Shahjahan Majib; Mahbubur Rahman; T.M. Shahriar Sazzad; Nafiz Imtiaz Khan; Samrat Kumar Dey, Year: 2021, "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images", IEEE Access, Vol: 09, pp. 116942-116952.

8. Zhenyu Tang; Yuyun Xu; Lei Jin; Abudumijiti Aibaidula; Junfeng Lu; Zhicheng Jiao; Jinsong Wu; Han Zhang; Dinggang Shen, Year: 2019, "Deep Learning of Imaging Phenotype and Genotype for Predicting Overall Survival Time of Glioblastoma Patients", IEEE Transactions on Medical Imaging, pp. 01-10.

9. Sohaib Asif; Wenhui Yi; Qurrat Ul Ain; Jin Hou; Tao Yi; Jinhai Si, Year: 2022, "Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images", IEEE Access, Vol: 10, pp. 34716-34730.

10. Wu Deng; Qinke Shi; Miye Wang; Bing Zheng; Ning Ning, Year: 2020, "Deep Learning-Based HCNN and CRF-RRNN Model for Brain Tumor Segmentation", IEEE Access, Vol: 08, pp. 26665-26674.

11. Gunasekaran Manogaran; P. Mohamed Shakeel; Azza S. Hassanein; Priyan Malarvizhi Kumar; Gokulnath Chandra Babu, Year: 2018, "Machine Learning Approach-Based Gamma Distribution for Brain Tumor Detection and Data Sample Imbalance Analysis", IEEE Access, Vol: 07, pp. 12-19.

12. Mohamed Shakeel.P; Tarek E. El.Tobely; Haytham Al-Feel; Gunasekaran Manogaran; Baskar.S, Year: 2019, "Neural Network Based Brain Tumor Detection Using Wireless Infrared Imaging Sensor", IEEE Access, Vol: 07, pp. 5577-5588.

13. Abdu Gumaei; Mohammad Mehedi Hassan; Md Rafiul Hassan; Abdulhameed Alelaiwi; Giancarlo Fortino, Year: 2019, "A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification", IEEE Access, Vol: 07, pp. 36266-36273.

14. Neelum Noreen; Sellappan Palaniappan; Abdul Qayyum; Iftikhar Ahmad; Muhammad Imran; Muhammad Shoaib, Year: 2020, "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor", IEEE Access, Vol: 08, pp. 55135-55144.

15. Andres Anaya-Isaza; Leonel Mera-Jimenez, Year: 2022, "Data Augmentation and Transfer Learning for Brain Tumor Detection in Magnetic Resonance Imaging", IEEE Access, Vol: 10, pp. 23217-23233.