Brain tumour detection from MRI images using machine learning and deep learning techniques

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ABSTRACT

The growth of abnormal brain cells, some of which may turn malignant, is what causes a brain tumour. Images from magnetic resonance imaging (MRI) are frequently used to detect brain tumours. The MRI images of the brain can be used to identify unusual tissue growth. Several research publications employ deep learning and machine learning algorithms to detect brain tumours. It is simpler to treat patients when brain tumours are swiftly and accurately identified using these algorithms in combination with MRI scans. These projections assist the doctor in making decisions. The radiologist can make decisions more quickly thanks to these projections. In the proposed work, we have used Support Vector Machine(SVM) and the M2 model is applied in detecting the presence of brain tumours.

Keywords: *Support Vector Machine, Convolution Neural Network, Machine Learning, Deep Learning, Brain tumour*

Introduction

The central nervous system distributes sensory data and actions throughout the body[1][2][3]. The spinal nerve and the brain aid in the spread. The major parts of the brain are the brain stem, cerebrum, and cerebellum[4]. A typical adult brain weighs approximately 1.4kg[5]. The brain's frontal lobe is involved in making judgements, controlling movement, and solving problems. The body orientation is controlled by the parietal lobe. The temporal lobe controls memory and hearing, whereas the brain's visual processing functions are coordinated by the occipital lobe. Cortical neurons make up the grey cerebral cortex cortex[6].

The cerebrum is bigger than the cerebellum in comparison and the cerebellum is in charge of controlling motor activities, which is the methodical supervision of free will in living beings with nerve systems. Due to the fluctuating size and stroke territory, the small lesion region cannot be found using the ALI, lesionGnb, or LINDA approaches. Comparatively, to other animals, humans have a cerebellum that is developed and well-structured[7].The cerebellum is divided into sections: the anterior, the posterior, and the flocculonodular. The vermis connects the posterior and anterior lobes. It is spherical in structure. White matter and an outer, greyish cortex that is thinner than the cerebrum make up the cerebellum. The anterior and posterior lobes assist in the coordination of complex motor activities. The organism's balance is maintained by the flocculonodular lobe[4][8]. The brain stem is a ten-centimetre-long stem-like structure. It has peripheral nerve bundles that aid in breathing and other essential processes like directing eye movements. The neuronal connections connecting the spinal cord and the thalamus meet at the brain stem. After that, they spread out over the entire body. The majority of the brain stem is made up of the medulla, pons, and midbrain. The midbrain supports functions like motor, auditory, visual, and

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motor thinking. The medulla oblongata supports breathing, intracranial transmission, sneezing, and other body activities, whereas the pons supports senses.

Our capacity for thought, voluntary movement, language, judgment, and perception are all functions of the brain, which is one of the body's most vital parts. Movement, balance, and posture are governed by this function. Without it, we would behave in a puppet-like manner. The Latin term for "small brain" is the origin of the name cerebellum. The development of a tumour in the brain, which can be innocuous (non-cancerous) or malignant, is what makes something a brain tumour. (cancerous). More frequently than original brain tumours, it can develop from metastases in brain tumours. Less than 2% of all cancer cases, or about 250,000 individuals annually, are affected by the majority of lung or breast cancer metastases. Brain tumours are the second most common cause of cancer in children and adolescents under the age of 15. For this reason, doctors frequently use magnetic resonance imaging (MRI) to examine brain tumour[9]. By using deep learning and machine learning techniques the analysis in this paper determines whether the brain is normal or abnormal.

2. Related works

In this study, an ANN-based model for the detection and classification of brain cancer was proposed.[10] Different techniques were used such as image processing, segmentation, and feature extraction in this method. In comparison to existing methods, the proposed method offers good classification accuracy. The proposed method was able to achieve good results and performed well in terms of computing.

CNN was used in this study[11] to to detect pituitary, meningioma, and glioma tumours with an overall accuracy of 91.3 per cent and recall of 0.81,0.88 and 0.99 respectively. Using two-dimensional CNN, a deep learning model is used in the detection of several forms of brain tumours from MRI image slices. Techniques like data preprocessing, pre-modelling, optimisation and hyperparameter tuning were used in this research.

[12] The technique used in this paper is based on Hough voting, a technique that allows for fully automatic segmentation and localization of the anatomies of interest. Additionally, it employed a segmentation strategy based on learning techniques that is reliable, multi-regional, versatile, and easily adaptable to many modalities. The model was trained on different dimensions of the dataset. The image is analysed using Hough[11] voting with CNN.

[13] The brain, a vital part of the human body controls and coordinates the functions performed by the other organs of the body. It is the central nervous system and is in command of carrying out the involuntary and voluntary functions of the body. The tumour is an uncontrolled growth of unusual tissue that forms a fibrous mesh inside of the brain. Magnetic resonance imaging is frequently used by doctors, and radiologists to examine the stages of tumours to prevent and treat the disease. This analysis's findings demonstrate the existence of the brain tumour.

A new framework for MAS for MRI tumour brain images is proposed by Zhenyu Tang et al[14]. In essence, MAS creates a new brain image for segmentation by recording and merging data from many normal brain atlases. Although the majority of its frames are for normal brain imaging, tumour brain images continue to be a challenging worry for it. At the first level of the MAS framework, a new algorithm is being used to retrieve the recovered picture of the normal brain from the MRI tumour brain image by using the information from the normal brain. The image is recovered without tumour interference in the following stage by registering a normal brain.

Baljinder Singh et al.[15] described a pre-processing step where noise is removed from the images using a fuzzy filter and a new mean shift-based fuzzy c-means algorithm that requires little computational time and produces better results than conventional methods. The typical fuzzy c-means objective function has a mean field phrase for the aforementioned segmentation strategies.

Meiyan Huang et al.proposed classifying the brain's voxel using the LIPC approach. The Path feature is also retrieved using this method. In LIPC, explicit regularisation is not required. The accuracy is low [16].

To diagnose brain tumours, Shamsul Huda et al. proposed a method using ensemble classification. Decision Tree, GANNIGMAC, and Bagging C-based wrapper technique are used to acquire decision rules, and the decision rules are made simpler by combining a hybrid approach with (Decision Tree + GANNIGMAC + Bagging C + MRMR C)[17].

3. Dataset

The dataset is taken from the Kaggle Brain tumour detection challenge 2020[18]. The dataset contains 3000 images in total. The dataset contains two folders yes and no. The yes folder contains 1500 images of MRI images which have tumours detected and 1500 images that were normal mri images which don't have any tumours detected.

The dataset is in the form of images of MRI. The dataset is divided for training and testing, 80% of the data is used for training the model and 20% is used for testing the model.

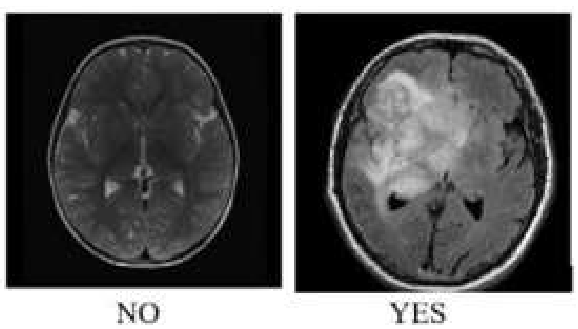

Fig. 1: Normal Brain and Brain with Tumor

4. Methodology

The two techniques SVM and the modified CNN are applied to the brain tumour dataset and their performance in classifying the image is analyzed.

Support Vector Machine

SVM[19] is a machine learning approach which is supervised. It is an algorithm that trains on specific data to make an accurate prediction on the testing data. The SVM algorithm is used for classification as well as regression, but it is mostly used for classification problems. The classification is done by finding a hyperplane that separates the two classes. For converting non-separable problems to separable problems SVM uses kernel trick which is used to convert lower dimension data into higher dimension data.

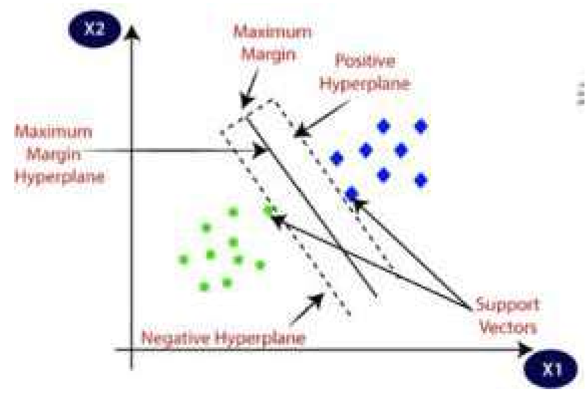

Fig. 2: Support Vector Machine[20]

Convolutional Neural Network

Our proposed M2 model is composed of several layers consisting of Convolution[21], Pooling, Dropout, Flatten, and Dense layers. The sequential model is used for adding the layers together. All the images are to a uniform size of 256x256. The input image is fed to the convolution layer with the relu as an activation function, with the same padding and the number of filters is 64,32,64,128,256 for the successive different convolution layers in the model. The max pooling applied with the 2x2 window size and dropout function is called with a 20% of dropout. The second last layer is the Dense layer which consists of 256 neurons and relu as the activation function. The last Dense layer consists of one neuron with a sigmoid activation function.

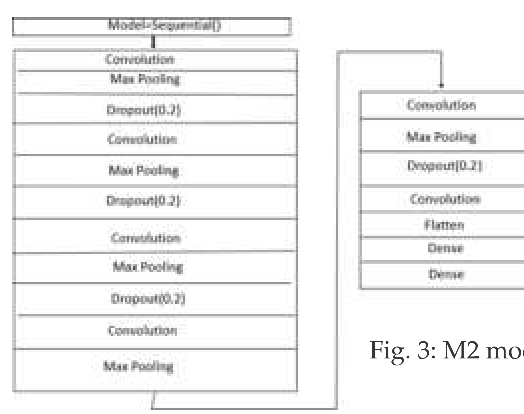

Fig. 3: M2 model

5. Experimental Result Analysis

TThe results of the models are shown in the below images, the M2 model is able to achieve a training accuracy of 98.58% and a testing accuracy of 97.67%. The model was trained for a few epochs. The support Vector Machine was able to achieve an accuracy of 97.33%. The confusion matrix plot is shown in the below plot

Fig. 4: M2 model accuracy and loss plot

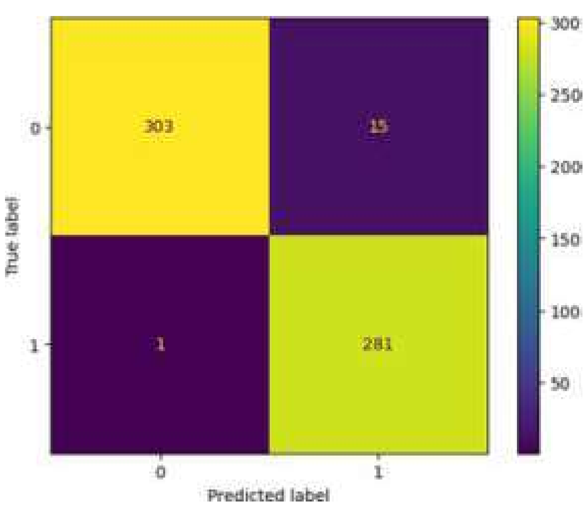

Fig. 5: Confusion matrix for SVM where 0 is representing the no tumor class and 1 is representing the tumor class

6. Conclusion

CNN is considered one of the best techniques for analyzing the image dataset. The model we used was able to achieve a testing accuracy of 97.67%. The SVM model generated here produces 97.33% of testing accuracy and this can be increased by training it on more image data. The classification accuracy can be increased by training the model on more data. In future work we can use optimization to decide the layers to be added to the model and various augmentation techniques can be used to increase the data.

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