Brain Tumor Detection and Tissue ClassificationUsing Machine Learning

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Abstract

Because of the complexity and diversity in tumours, this method is unfeasible for a biggerset of data, and the tumour detection procedure is a difficult effort. The paper's main goal is to use Magnetic Resonance Imaging (MRI), Image Pre-processing, and Machine Learning algorithms to create a model for detecting brain cancers. Human inspection is the traditional approach for finding cancers. This research attempts to create an automated method that can be used to determine whether or not a lump in the brain exists. Before an image is processed into an application, image pre-processing techniques are employed to increase its quality. For each MR picture,
pre-processing is utilized to extract image patches. The accuracy of proposed method is 95.50%. We have used a total number of 1720 samples out of which we have used 400 for testing our model.

Keywords - Magnetic Resonance Imaging, Brain tumor detection, Image Pre-processing, Machine learning.

Introduction

A key background for the rapid increase in mortality among children, adults, and especially the elderly is recognised to be brain tumours. Because the human body is made upof millions of cells, we know that they proliferate, grow, and divide to generate new cells and tissues. External causes may cause the cells to proliferate uncontrolled, resulting in tumour growth. Tumors are classified as benign or malignant. Benign tumours are cancerous cells that do not spread to other cells. Malignant tumours, on the other hand, are masses of cancerous cells that are dangerous and more prone to spread to other cells and organs. We classified three types of tumours in this project: pituitary tumour, glioma tumour, and meningioma tumour. according to international statistics, the United States has an increasing rate of tumour probability over time, with 11 percent to 12 percent of people diagnosed with cancer every year. Human examination is the traditional approach for detecting tumours in MRI images. supervised approaches such as convolutional neural networks are used to classify MR human brain pictures.Noise from operator intervention isalso present in the MRI, which can lead to incorrect classification. a large amount of MRI must be analysed, necessitating the use of automated technologies, which are more cost-effective. Because great precision is required when dealing with human life, automated tumour diagnosis in MRI images is required. Both supervised and unsupervised algorithms can beused to classify MR pictures as normal or abnormal.

In this research, machine learning methods areused to provide an efficient automated categorization technique for brain MRI. Brain tumours are classified using an MRI image using a supervised machine learning system.

Literature Survey

1. MRI based medical image analysis: Surveyon brain tumour grade classification.

[5] This paper's goal is to provide a review of recent brain magnetic resonance (MR) image segmentation and tumour grade classification techniques. The tumour may appear clear on Magnetic Resonance Imaging (MRI), but clinicians need to quantify the tumour area for further therapy. This is where digital image processing approaches and machine learning come together to help with further diagnosis, therapy, and pre- and post-surgical procedures, resulting in a synergistic relationship between the radiologist and the computer. These hybrid techniques give radiologists a second opinion and help them grasp medical images, enhancing diagnostic accuracy. The goal of this paper is to look back on current trends in segmentation and classification for
tumor-infected human brain MR images, with a focus on gliomas, such as astrocytoma. The methods for extracting and grading tumours are described, and they can be integrated into regular clinical imaging processes. Finally, a critical evaluation of the current state of the art, prospective advances, and trends is presented.

2. Human-Expert-Level Brain Tumour Detection Using Deep Learning with Data Distillation and augmentation

[6] Two issues frequently obstruct the use of Deep Learning (DL) for medical diagnosis. First, because the number of people who have developed the illness is small, training data may be insufficient. Second, numerous sources of noise may distort the training data. We look at the challenge of brain tumour identification using magnetic resonance spectroscopy (MRS) data, which has both types of issues. To address these issues, we offer a new approach for training a deep neural network that separates out the most representative training instances and augments the training data by combining samples from one class with samples from other classes to create additional training samples. We show that using this methodology boosts performance significantly, allowing our system to achieve
human-expert-level accuracy with only a few thousand training samples.

3. Brain Tumour Detection and Classification based on Hybrid Ensemble Classifier

[7] Early detection of brain tumours is critical for improving patient survival and treatment success. Manually evaluating magnetic resonance imaging (MRI) images is a tough undertaking. As a result, more accurate digital approaches for tumor diagnostics are required. However, determining their structure, volume, borders, tumor detection, size, segmentation, and classification remains a difficult task. We present a hybrid ensemble technique based on the Majority Voting Method that uses Random Forest (RF),
K-Nearest Neighbour, and Decision Tree (DT) (KNN-RF-DT). Its goal is to calculate the tumour's area and classify benign and malignant brain tumours. at first, Otsu's Threshold approach is used to segment the data. The thirteen characteristics for classification are extracted using the Stationary Wavelet Transform (SWT), Principal Component analysis (PCa), and Gray Level Co-occurrence Matrix (GLCM). Based on the Majority Voting approach, a hybrid ensemble classifier (KNN-RF-DT) is used to classify the data. Rather than using deep learning, it tried to improve the performance of classical classifiers. Traditional classifiers offer an advantage over deep learning algorithms in that they require less datasets for training, have a lower computational time complexity, are less expensive for consumers, and can be easily adopted by persons with less training experience. Overall, we tested our suggested technique using a dataset of 2556 images, which were split 85:15 for training and testing and gave a good accuracy of 97.305%.

4. Analysis of Brain MRI Images Using Improved Corner Net approach

[8] The brain tumour is a life-threatening condition produced by aberrant brain cell proliferation that affects human blood cellsand nerves. Brain tumour diagnosis that istimely and precise is critical in order to prevent complex and unpleasant treatment procedures, as it can aid surgeons in surgical planning. Manual brain tumour identification takes time and is mainly reliant on the availability of local experts. as a result, accurate automated techniques for the identification and categorization of diverse forms of brain tumours are urgently needed. However, due to wide differences in size, position, and structure, precise localization and categorization of brain tumours is a difficult task. To address the issues, we proposed a unique technique called the
DenseNet-41-based Corner Net framework. Three steps make up the proposed solution. To begin, we create annotations to pinpoint the particular region of interest. The deep features from the suspected samples are extracted in the second stage using a modified Corner Net with DenseNet-41 as the foundation network. The one-stage detector Corner Net is used to locate and classify numerous brain tumours in the final step. We used two databases to test the proposed method: the Fig share and Brain MRI datasets, and achieved average accuracy of 98.8 percent and 98.5 percent, respectively. Our approach is more proficient and consistent than other recent strategies in detecting and classifying distinct forms of brain tumours, according to both qualitative and quantitative research.

Proposed Methodology

This section depicts the proposed framework for detecting brain tumours. The goal is to automatically recognise and diagnose the brain tumour for a given input sample without requiring any operator involvement. The steps of our job are as follows: To begin, we prepped the dataset by adding annotations to the input photos to pinpoint the exact position of tumours. The model was then trained using the newly created annotations for tumour classification and localisation.

The process takes place as follows:

Image acquisition: The MRI brain images are acquired and are given as input to
pre-processing stage.

Pre-processing: Pre-processing is needed as it provides improvement in image data which enhances some of the image features which are important for further processing. The
pre-processing steps that are applied to MR image are as follows:

I. The RGB MR image is converted to grayscale image and then median filter is applied for noise removal from brain MR images. The noise is removed for further processing as high accuracy is needed.

II. Then edges are detected from the filtered image using canny edge detection. The edge detected image is needed for segmentation of the image.

III. Then watershed segmentation is done for finding the location of the tumour in the brain image. Segmentation is the process of dividing an image into multiple segments. The aim of segmentation is to change representation of image into something which is easier to analyse. The result of watershed segmentation is label image. In label image, all the different objects identified will have different pixel values, all the pixels of first object will have value 1, all the pixels of second object will have value 2 and so on. The various
pre-processing operations applied on brain MR images. Pre-processing operations on input brain image.

Feature Extraction: When input to an algorithm is very large and redundant to be processed, it is transformed into reduced representative set of features called feature vector. Transformation of input data into set offeatures is called feature extraction. In this step, the important features needed for image classification are extracted. The segmentedbrain MR image is used and texture features are extracted from the segmented image which shows the texture property of the image.

Classification: The Machine learning algorithms are used for classification of MR brain image either as normal or abnormal. Themajor aim of ML algorithms is to automatically learn and make intelligent decisions.

The human brain is modelled using neural network architecture and implementation. Vector quantization, approximation, data clustering, pattern matching, optimization functions, and classification algorithms are all common uses for neural networks. The interconnections of a neural network split it into three types. There are three types of neural networks: feedback, feed forward, and recurrent. The Feed Forward Neural Network is separated into two types: single layer and multilayer. The hidden layer is not visible in asingle layer network. However, it just has an input and output layer. The multilayer, on the other hand, is made up of three layers: input, hidden, and output. The recurrent network is a closed loop-based feedback network. Image scalability is not possible in a traditional neural network. However, in a convolution neural network, an image can be scalable (thatis, it can go from a 3D input volume to a 3D output volume) (length, width, height). The input layer, convolution layer, Rectified LinearUnit (ReLU) layer, pooling layer, and fully connected layer make up the Convolution Neural Network (CNN). The given input image is divided into small sections in the convolution layer. The ReLU layer performs element-by-element activation. The pooling layer is not required. We can choose to use or skip. The pooling layer, on the other hand, is mostly utilised for down sampling. The class score or label score value is generated in the last layer (i.e. fully connected layer) based on the likelihood between 0 and 1. The brain tumour classification block diagram based on convolution neural network is shown in fig.1. The training and testing phases of the
CNN-based brain tumour categorization are separated. The number of images is separated into several categories by labelling them, suchas tumour and non-tumor brain images, and so on. To create a prediction model,
pre-processing, feature extraction, and classification with the Loss function areconducted in the training phase. Label the training image set first. Image resizing is used in pre-processing to adjust the image's size.
Finally, a convolution neural network is employed to automatically classify brain tumours. Image net provided the brain image dataset. One of the pre-trained models is Image Net.If you wish to train from the beginning layer, you must train the completelayer (all the way to the conclusion). as a result, time consumption is extremely high. It will have an impact on performance. For classification phases, a pre-trained
model-based brain dataset is used to circumvent this problem. Only the last layer of the proposed CNN will be trained in Python. We don't want to train each layer individually. as a result, the suggested automatic brain tumour classification technique has a short calculation time yet a high performance.The gradient descent algorithm is used to calculate the loss function. Using a score function, the raw image pixel is mapped to class scores. Theloss function is used to assess the quality of a set of parameters. It is determined by how closely the induced scores matched the training data's ground truth labels. To enhance accuracy, the loss function calculation is crucial. When the precision is low and the loss function is high. Similarly, when the loss function is low, the accuracy is high. To compute the gradient descent algorithm, the gradient value is calculated for the loss function. To compute the gradient of the loss

function, evaluate the gradient value repeatedly.

Algorithm for CNN based Classification

1. apply convolution filter in first layer

2. The sensitivity of filter is reduced by smoothing the convolution filter (i.e.) subsampling

3. The signal transfers from one layer to another layer is controlled by activation layer

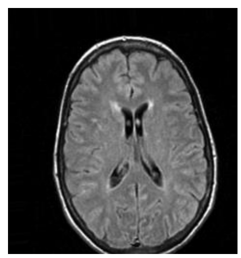
4. Fasten the training period by using rectified linear unit (RELU)

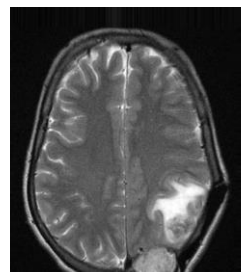
4. The neurons in proceeding layer is connected to every neuron in subsequent layer

5. During training Loss layer is added at the end to give feedback to neural network

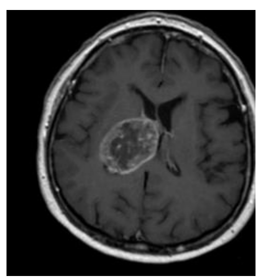
The primary purpose of this study is to develop an efficient automatic brain tumour classification system with high accuracy,speed, and simplicity. Traditionally, brain tumour classification is done using Fuzzy C Means (FCM) based segmentation, texture and shape feature extraction, and SVM and DNN based classification. The level of difficulty is low. However, the computation time is long, and the precision is poor. a convolution neural network-based classification is included in the suggested system to improve accuracy andreduce computation time. The classification results are also labelled as either tumour or normal brain images. CNN is a deep learning approach that consists of a series of feed forward layers.Python is also used in the implementation. For classification, an image net database is used. It's one of the models thathas already been trained. as a result, just the last layer gets trained. CNN also extracts raw pixel values with depth, width, and height feature values. Finally, to obtain high precision, the Gradient descent based loss function is used. The validation accuracy, validation loss, and training accuracy are all calculated. The accuracy of the training is 97.5 percent. Validation accuracy is also excellent, and validation loss is minimal.

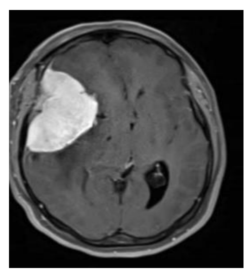
Figure	Image Description
A	Normal Brain
B	Pituitary Tumour
C	Glioma Tumour
D	Meningioma Tumour





A B

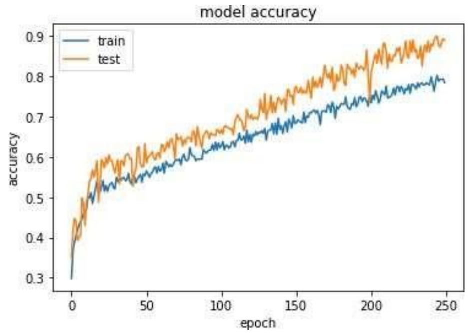


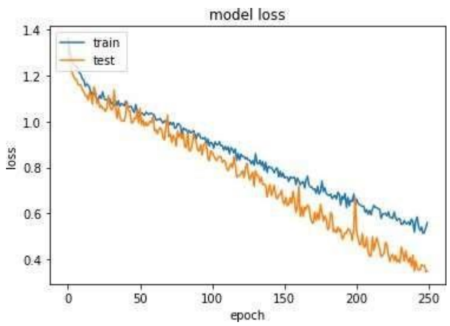


C D

Result

This experiment was carried out on 1720 brain MR images. The texture based features are extracted for each image. We have used total 1720 images for training .after that we havetested our model and we got more accuracy than in our training phase that is- 95.50%.and loss in the model were also reduced.





CNN Classification rate table:

ML algorithm	Total Samples	Testing Samples	Training Samples	Classification Rate(%)
CNN	1720	400	1320	95.50%

Conclusion

This research presents a system for detecting brain tumours using machine learning algorithms. Grey Level Co Occurrence Matrix is used to extract texture-based information.

Energy, contrast, correlation, and homogeneity are textural aspects of the image evaluated in this suggested work. Convolutional neural network machine learning algorithm is utilized for classification, with a maximum accuracy of 95% attained by considering 1720 samples. a larger data collection would very certainly improve this accuracy.

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