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Multiclass Brain Tumor Detection and Classification Using Deep Learning Techniques

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ABSTRACT
Brain tumor is a severe cancer and a life-threatening disease. Thus, early detection is crucial in the process of treatment. Recent progress in the field of deep learning has contributed enormously to the health industry medical diagnosis. Convolutional neural networks (CNNs) have been intensively used as a deep learning approach to detect brain tumors using CT brain images. Due to the limited dataset, deep learning algorithms and CNNs should be improved to be more efficient. Thus, one of the most known techniques used to improve model performance is Data Augmentation. CNN classifier used to compare the trained and test data, from this we can get the classified result for tumor. The experimental results of proposed technique have been evaluated and validated for classification performance on magnetic resonance brain images, based on accuracy, sensitivity, and specificity. Detection, extraction and classification of tumor from CT brain images of the brain is done by using Python.

Keywords : Convolutional Neural Networks, CT Brain, Brain Tumor

I. INTRODUCTION

The Medical image processing can be defined as picturing of body parts, tissues or organs for clinical analysis and treatment. It is one of the technique used to create an images of the human body. Imaging techniques are in the fields of radiology, nuclear medicine and optical imaging. The medical image processing consist of display of an image, enhancement, and analysis that captures an image through instruments like MRI (Magnetic Resonance Imaging), X-ray, Nuclear medicine, Ultrasound, optical imaging, and Computed Tomography (CT) scanners respectively.

The medical imaging systems are used to analyses the human body in both macro and micro level such as organ level and cellular correspondingly. Medical image processing is a highly challenging research area. The internal parts of the human body are diagnosed through medical imaging technique. Medical imaging have high importance because of correct diagnosis and treatment of diseases in health care system. The image of internal body parts where produced by the equipment’s like CT scanner, MRI. These images are assigned with composed pixel of discrete brightness and colour values.

II. PROBLEM STATEMENT

• Limited number of training samples are available and accuracy of classification is not high.

• The technique's performance on the boundaries between different regions is relatively poor.

• The algorithm complexity of training and testing on the datasets is high.

OBJECTIVES

• To perform pre-processing by using median filter for the removal of noise and enhancing the quality of input image.

• To perform efficient data augmentation by altering the existing data to create more data for the model training process.

• To perform efficient classification of brain tumour detection with the help of CNN for the generation of accurate and improved outputs.

LITERATURE REVIEW

Jiangjun Peng et al [2020] propose an enhanced 3DTV (E-3DTV) regularization term beyond the conventional. Instead of imposing sparsity on gradient maps themselves, the new term calculates sparsity on the subspace bases on gradient maps along all bands of an HSI, which naturally encodes the correlation and difference among all these bands, and thus more faithfully reflects the insightful configurations of an HSI. The E-3DTV term can easily replace the conventional 3DTV term and be embedded into an HSI processing model to ameliorate its performance.

Yunping Mu et al [2019] Speckle noise removal problem has been researched under the framework of regularization-based approaches. The regularizer is normally defined as total variation (TV) that induces staircase effect. Although higher-order regularizer can conquer the staircase effect to some extent, it often leads to blurred. Considering the upper questions,

The combination of first and second-order regularizer will be an effective and prior method to tackle speckle noise removal. So a variational model with hybrid TV and higher-order total curvature (TC) term is proposed in this paper, the data fidelity term is derived based on G 0 distribution. In order to preserve the edge detail better, the boundary detection function is combined with the regularizer. Furthermore, the Mellin transform is used to estimate the parameters of the model. To address the speckle noise removal optimization problem, alternating direction method of multipliers (ADMM) framework is employed to design a convex numerical method for the proposed model. The numerical method can be used to update the variables flexibly as required by the hybrid regularizer.

EXISTING SYSTEM

• In this system, we proposed a novel deep learning denoising framework aiming to enhance the quantitative accuracy of dynamic PET images.

• This is done via introduction of deep image prior (DIP) combined with Regularization by Denoising (RED), as such the method is labeled as Deep RED denoising.

• The network structure is based on encoder-decoder architecture and uses skip connections to combine hierarchical features to generate the estimated image.

• Based on simulated data and real patient data, the quantitative performance of the proposed method was compared with state-of-the-art methods. The comparison study proves that several limitation are existed.

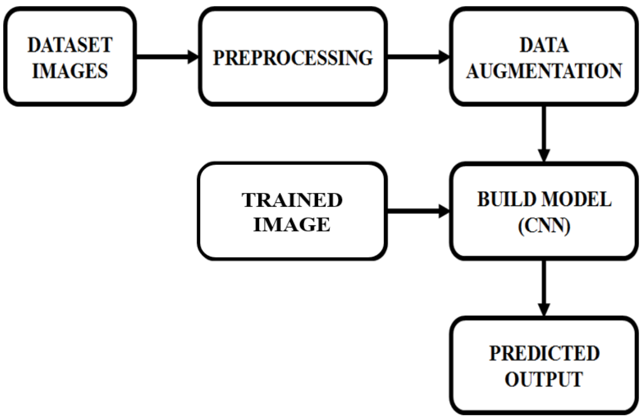
DRAWBACKS

• Accuracy of the results are very low.

• The time taken for training and testing data are more.

• The computational complexity of data is too high.

PROPOSED SYSTEM BLOCK DIAGRAM



DATASET

```
826 glioma_tumor images
822 meningioma_tumor images
395 no_tumor images
827 pituitary_tumor images
```

CNN CLASSIFICATION

• CLASSIFICATIONS: Convolutional Neural Networks (CNN) are deep learning algorithms that are very powerful for the analysis of images.

• There are three types of layers in Convolutional Neural Networks:

1. Convolutional Layer
2. Pooling Layer
3. Fully-Connected layer

CNN ALGORITHM

• Classification of Brain Stroke using Convolution Neural Network

• Input: Load all CT images *I* from the dataset

• Output: Classified brain stroke images (CI) into hemorrhagic and ischemic

• Step 1: Function CI=Classify (I)

• Step 2: Apply contrast stretching

• Step 3: Perform image filtering using average filter with image sharpening procedure

• Step 4: Use quad tree based image fusing technique by fusing contrast and filtered image

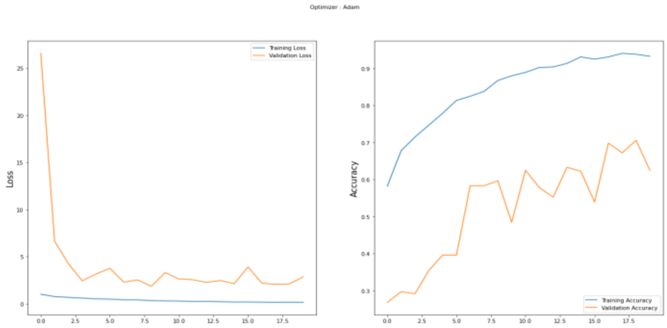
• Step 5: Partition the fused image dataset into training and testing set

• Step 6: Feed the training dataset of 512 × 512 × 1 into P_CNN network

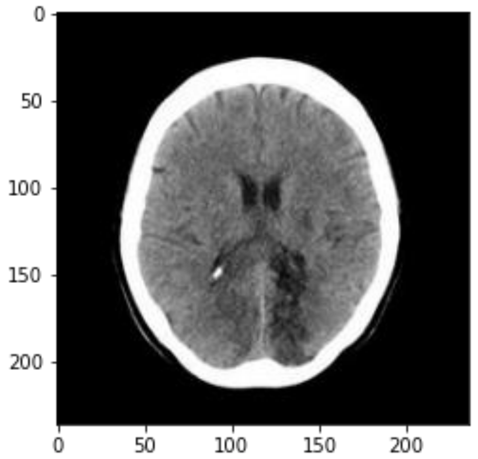
1. ReLU layer
2. MaxPooling layer
3. 2-D convolutional layer with 10 filters of [5 5]
4. 2-D convolutional layer with 96 filters of [11 11] size where stride is 4.
5. ReLU Layer
6. MaxPooling layer
7. Fully connected layer with output size of 512
8. ReLU Layer
9. Dropout layer with dropout probability 0.1
10. Fully connected layer with output size of 2 to classify stroke as hemorrhagic or ischemic
11. Apply softmax layer

Classify image dataset using classification layer

ACCURACY AND LOSS

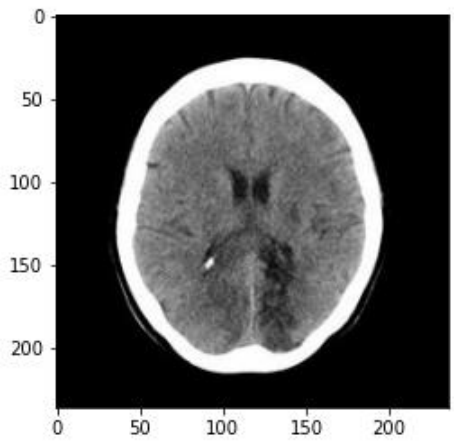


TESTIMAGE

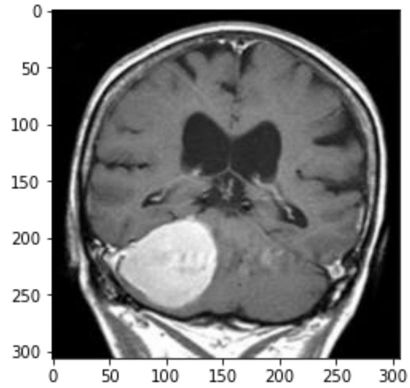


PREDICTED OUTPUT

```
Out[19]: 'no_tumor'
```

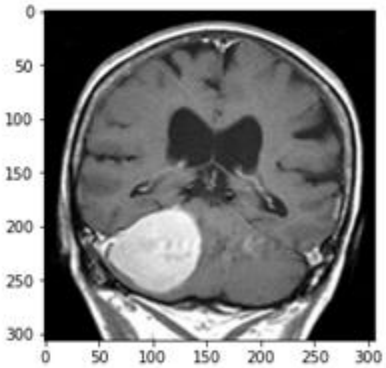


TEST IMAGE

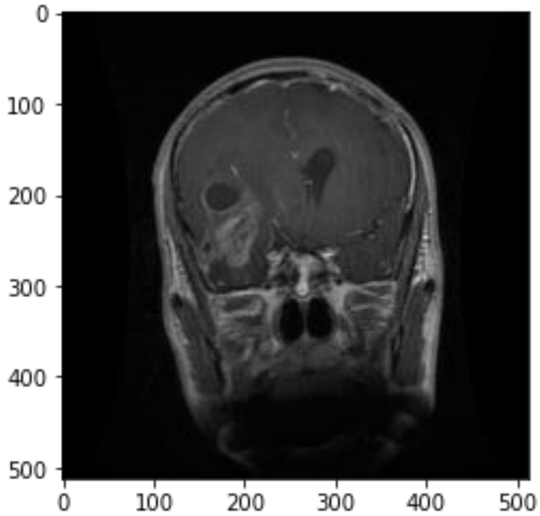


PREDICTED OUTPUT

Out[20]: 'meningioma_tumor'

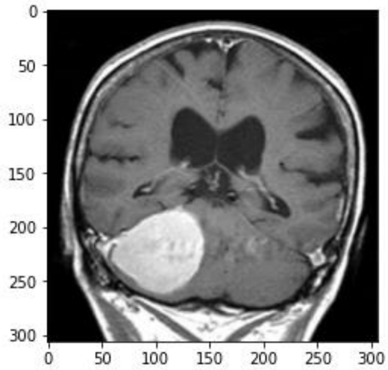


TESTIMAGE

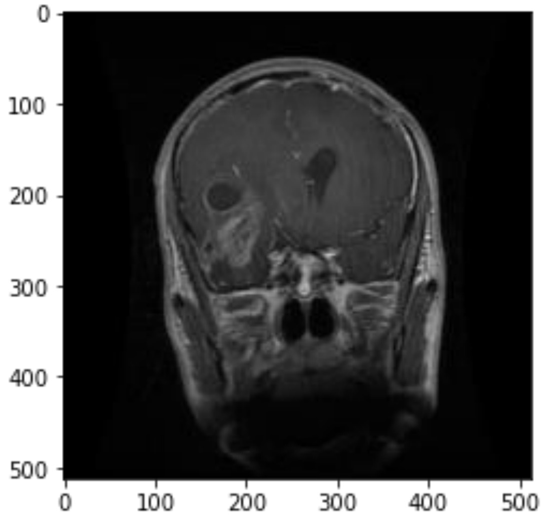


PREDICTED OUTPUT

Out[20]: 'meningioma_tumor'

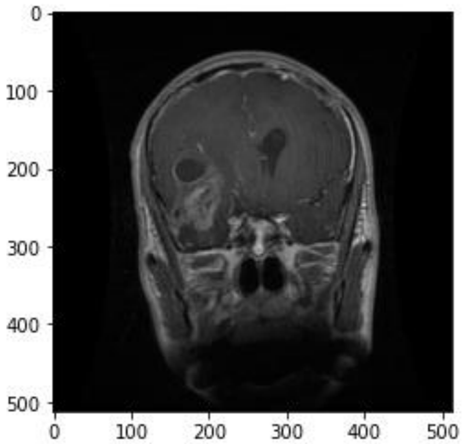


TESTIMAGE

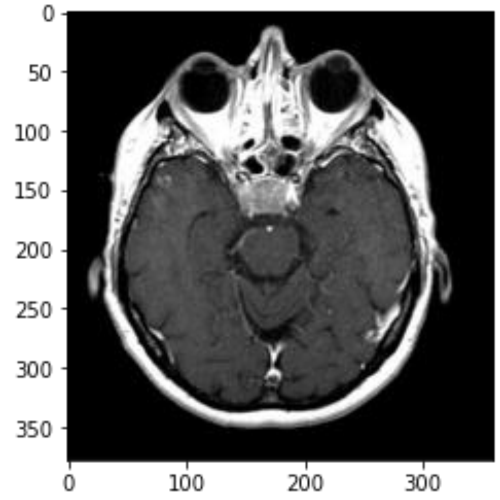


PREDICTED OUTPUT

Out[29]: 'glioma_tumor'

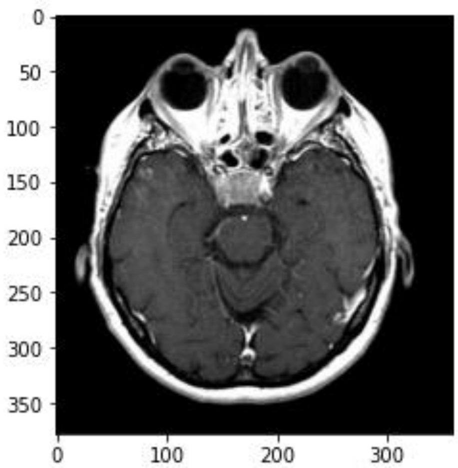


TESTIMAGE



PREDICTED OUTPUT

```
Out[23]: 'pituitary_tumor'
```



ADVANTAGES

Time consumption is low.

Accuracy of the results is high.

Computational complexity of the algorithm is low.

APPLICATIONS

Image Polishing and restoration.

Small Lesion Detection

Image Segmentation

CONCLUSION

In this Project, we proposed a deep learning convolutional neural networks framework to get exact haemorrhage segmentation in CT brain images. Initially, for the input of the network, data symmetry, and data augmentation are considered in the proposed model to abstract the structural symmetry of the brain image and prepare enough training data. Second, median filter is used to segment the interest area from the background. Comparing the experiments based on CT brain images demonstrated that the proposed CNN based model shows great advantages compared with human experts on haemorrhage lesion diagnosis.

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