DBN: A Robust Model For Brain Tumour Analysis Using Deep Learning Brain-Net

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Abstract- *Brain tumour becomes one of the serious disease in today's life style that leads to loss of life and cases with certain severe stages enrol the lack of feasibility in recovering the disease. In many existing literature references, brain tumour detection through image processing is discussed. The proposed work is focused on detection and analysis of various brain tumour stages using ATLAS (Anatomical Tracings of Lesions after Stroke) dataset. The system architecture consists of pre-processing stage, feature extraction through GLCC matrix for extraction of statistical features of the test case images. CT and MRI images are combined and used. Heterogeneity, Co-variance are the features extracted and mapped. The proposed Brain-Net using the convolution neural network is derived to adopt the input dataset that are pre-trained and labelled with the ground truth variables. The proposed system achieves enhanced performance in terms of speed using the Google colab environment that internally adopts the python libraries. The proposed system achieves accuracy of 99.8% and the average loss function of 0.10692T.*

Keywords- Deep learning network, machine learning, image processing, brain tumour detection, brain tumour analysis, image fusion, image segmentation techniques.

I. INTRODUCTION

In the current changing life style, rate of diseases got increased in a forward graph. Tumour is one of the serious disease that directly hit the life span of the human beings. Tumour can occur at any region of the body, perhaps the brain tumour seems to be the most dangerous one since the percentage of survival rate is too low and the diagnosis procedures that is required to cure the brain tumour is least feasible. The unhealthy brain cells can also directly cause the tumour. Tumours are classified into primary type and secondary type. The tumour that is non-cancerous is nature is called as the benign tumours. The type that is highly stores the cancerous cells are further represented as malignant tumours.
In the field of medical diagnosis procedures, digitally scanned images plays a vital role is finding the position of the region where the tumour cells are formed. Most commonly used medical images are MRI and CT scan images. X-Rays are used in the initial stage of the diagnosis. To extract the accurate internal structure of the brain, MRI scanning is used because of its higher resolution in screening. After the screening images, the infected area need to be segmented properly using image segmentation methods in digital image processing.

Image fusion is one of the commonly used technique in image processing to consider the multi-spectral images. In many cases to find out the accurate marking of the infected area, fusion of images of different spectral frequency is required and that is processed using the image fusion method with various algorithms.

Many advanced methodologies are evaluated for the purpose of classification and feature extraction of the brain images. Since finding the normal brain and abnormal brain depends upon the uniqueness present with the brain data that is being processed. Many learning algorithms that support the classification of brain tumour such as (ANN) Artificial neural network, (KNN) K-Nearest neighbour, (SVM) Support vector machines. Deep learning algorithms are used in today's research works for the accurate evaluation of brain tumour. Convolution neural network (CNN) is one among the algorithm that is considered as robust detection model. Deep learning algorithms are meant for complex connections between the features.

A proper dataset is important for any kind of model development. Furthermore, here in our proposed system, python is the tool used for image analysis. Python with tensor flow library is utilized to create the robust prediction model. For the purpose of testing, ATLAS (Anatomical Tracings of Lesions after Stroke) dataset is considered. For experimental results we used convolutional neural network and super pixel based feature extraction algorithms. In the present paper work, SEC I provides the introduction on brain tumour and methodologies adopted as overview. SEC II discuss the various literature background considered for the selection of algorithm and methodologies. SEC III discuss the system design and specification of tools. SEC IV discuss the proposed architecture and flow of implementation. SEC V shows the experimental results obtained.

II. LITERATURE SURVEY

[[1] the author proposed the concept of 3 dimensional CNN architecture that uses the multi-modality of fusion technique to extract the features of the brain images. The author focused on reducing the loss function. The proposed methodology extract the tumour lesions and quantitative measurements are done through correlation coefficient, sensitivity and specificity. The archived output images after the convolution neural network process in 3D, the images are sliced and displayed as 3D structure.

[2] The author developed a inception-v3 based deep dense network protocol for extracting various features. The feature from different inception modules are extracted from the inception V3 architecture. DenseNet201 is utilized here for the accurate prediction of tumour. For the given dataset, about 99.5 % of accuracy is achieved with the testing of pre-trained models. Comparison of inception V3 modules and Deep Dense-Net is evaluated.

[3] Based on MRI images, the optimized techniques are evaluated using (GA) genetic algorithm. The input image data is considered to be more important in accurate segmentation of the tumour. Fractional order threshold filters are utilized before applying the genetic algorithm. Balanced contrast enhancement technique is utilized for the extraction of the brain image unique points and detect the fine edges of the tumour part.

[4]The author utilized BRAT2017 dataset for the evaluation of patch based processing of tumour using neural networks. An automated brain tumour detection system is utilized in order to cascade and segment the low grade Glioma and high grade Glioma. Based on the non-linear activation function, the features are uniquely extracted and labelled as per the database.

[5] Hybrid dual tracking system encapsulated with U-Net protocol is utilized here for the purpose of treating the MRI images. However the challenging problem is to achieve well performing system with higher accuracy is formulated. By varying the different kernel of the convolution filters, different loss functions are evaluated.

[6] A novel stacked framework is evaluated by which the stacked multi-connection simple reducing network is developed. The Stacked network is derived from the U-Net. In order to obtain better segmentation performance by tuning the U-Net, stacked networks are utilized. Reduced feature size always improve the performance of the network model during classification.

[7] A brain tumour segmentation using heterogeneous Convolution neural network (HNN) is presented by the author. It uses HCNN for image patches. In this system, a detailed working mechanism is adopted in which patches of images are processed independently and finally the segmented models are coordinated. Their experimental results achieve better performance in all Spectral images of scans.

III. SYSTEM DESIGN

Python is the high level computing tool with user friendly interfaces and library calling functions. The tool is adoptable to working environment, here in this case, 200 images of tumour infected brain images and normal images are need to be processed. Google colab is the notebook environment that perform the entire operations in the cloud. Colab is the integrated environment that support Python libraries such as Pytorch, Keras, TensorFlow and openCV. Zero configuration is required to start with the colab environment. It can support hassle-free GPU access, also support easy sharing and configurations. Google support is frequently used for machine learning algorithms that need to be implemented in the analysis of real time inputs. Google colab with the Jupiter notebook environment support our proposed work that analysed within the cloud itself.

A. *Dataset*

Anatomical Tracings of Lesions after Stroke (ATLAS) R1.1 is the dataset considered for the proposed analysis. ATLAS (Anatomical Tracings of Lesions after Stroke), an open-source dataset of 229 T1-weighted MRI scans (n=220) with physically segmented scratches and metadata. This great, assorted dataset can be recycled to train and test lesion segmentation algorithms and affords a homogenous dataset for associating the presentation of different separation devices.

IV. DESIGN METHODOLOGY

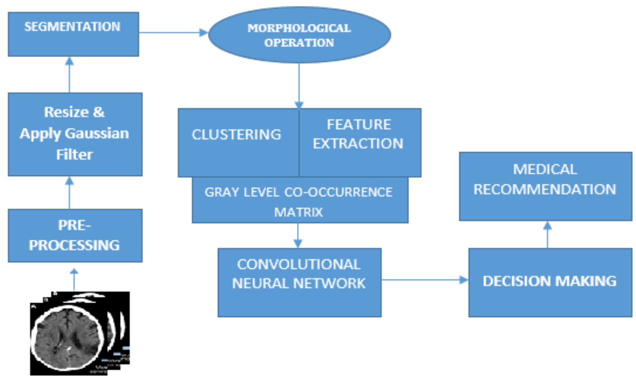

Fig 1. System architecture of Proposed Deep Convolution Neural Network (Brain-Net)

B. *Preprocessing*

The preprocessing section of the system read the test image from the ATLAS dataset and converts the image into grayscale. Most of the scanned images are gray in nature, in case of MRI images or other high resolution the gray scale conversion is required. The images are also resized to make it constant sized for flexible processing.

C. *Filtering*

Gaussian filter is used here. It has the property of special pulsed filtering property. Hence the property is specified by the corner attenuation and additional parameters are used. The Gaussian filter is better than other methods because of the optimal reducing of noise (blur area) in spatial domain.

Segmentation

Morphological segmentation is the broad set of image processing in which the shapes are extracted from the structured elements based on shapes. Morphology is normally located using the objects and boundaries. The methodology is used for the image segmentation, noise suppression, feature extraction and other image processing techniques.

D. *Feature Study*

The input images are feature extracted using Gray level co-occurrence matrix and clustering methods. The gray level extraction reads the heterogeneity, sensitivity and various other statistical features of the input test image. Features extracted variables are feature mapped before fetching it into the Convolution neural network.

E. *Deep Brain-Net*

Convolution neural network developed here is tuned to adopt the input test images of ATLAS dataset. The images of 200 numbers with brain tumour infected images and normal images are considered for the input. The convolution neural network contains input layer, softmax layer, maxpooling layer and fully connected layer. The performance of the system is measured by plotting the confusion matrix to attain True positive rate, True negative rate, false positive rate and false negative rate etc.

Deep Brain-Net architecture

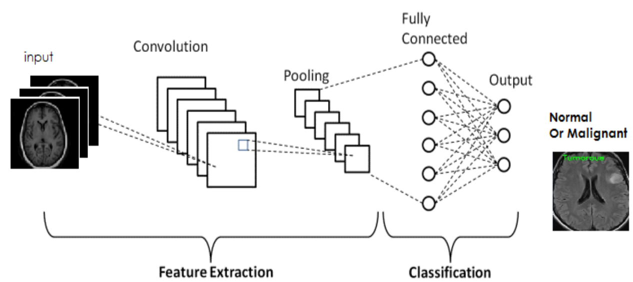

Fig 2. Deep Brain-Net architecture

F. *Process of Kernel Filters*

Fig 3 shows the clear depiction of kernel filters of the Deep Brain-Net where the input images and their features are uniquely mapped using the kernel filter and Soft max layers of the model.

Layers of Deep Brain-Net using Dense CNN

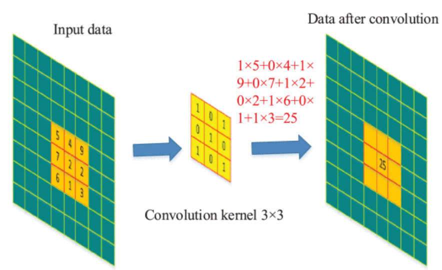

Fig 3. Processing of Kernel filters

```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 240, 240, 3)       0
zero_padding2d (ZeroPadding2 (None, 244, 244, 3)       0
conv0 (Conv2D)               (None, 238, 238, 32)      4736
bn0 (BatchNormalizationV1)   (None, 238, 238, 32)      128
activation (Activation)      (None, 238, 238, 32)      0
max_pool0 (MaxPooling2D)     (None, 59, 59, 32)        0
max_pool1 (MaxPooling2D)     (None, 14, 14, 32)        0
flatten (Flatten)            (None, 6272)              0
fc (Dense)                   (None, 1)                 6273
-----------------------------------------------------------------
```

SIMULATION RESULTS

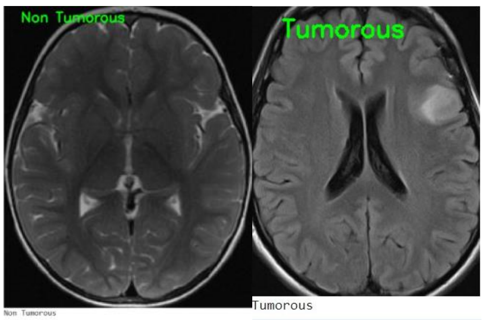

Fig 4. Simulation results of Deep Brain-Net detecting the Tumourous and Non-Tumourous images with Labels

Table 1. Table showing the obtained statistical results during training

Epoch	Loss	Accuracy	Val-Loss	Val-Acc
1	0.0899	0.9785	0.331	0.8935
2	0.1343	0.9509	0.517	0.8258
3	0.1137	0.9626	0.695	0.7516
4	0.1018	0.964	0.321	0.9065
5	0.0949	0.9689	0.425	0.8484

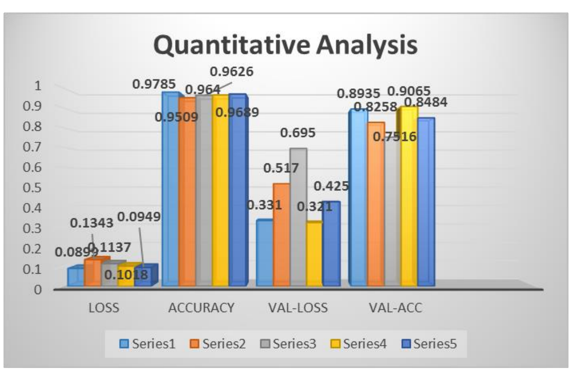

Fig 4. Graphical chart showing the quantitative analysis

Table II. Evaluation results of Various Test Cases using Deep Brain-Net architecture

Test case no	Description	Pre-conditions	Pass /Fail	Expected results
SK_001	User input the image	Check the input image condition	Pass	Image Acquisition is calculated
SK_002	Pre-processing the images	Avoid the noise & image enhancement	Fail	Image not resize
SK_002a	Pre-processing the images	Avoid the noise and Gray-level or spatial quantization	Pass	Image is resize
SK_003	Feature Extraction using super pixel algorithm	Parameter values are extracted from the images	Pass	Successfully values are extracted from the images
SK_004	Machine learning technique	Training model generation	Pass	Training dataset generated
SK_005	Machine learning technique	Test the input image	Pass	Compare with the trained model
SK_006	Normal / Malignant node Detection	Normal or tumour detected	Pass	Tumour detected by percentage analysis
SK_007	Medicine Prescription	Compare with the trained dataset	Pass	Medicine Recommendation

Accuracy

The accuracy of the proposed model is calculated using the number of correctly evaluated results with the total images intended for analysis. The proposed system achieved 99.86% of accuracy on both the classification of tumorous and non-tumorous images.

V. CONCLUSIONS

Deep learning based brain tumor analysis is evaluated using ATLAS dataset. The dataset is the combination of tumorous and non-tumorous images of high resolution category. The proposed system uses GLCM for feature extraction and Deep Brain-Net derived from Convolution neural network for implementing the detection and classification of brain images. The lesser the features that are extracted uniquely, the higher the feasibility on accurate prediction. The convolution net is tuned in such a way it can adopt the customized input ATLAS dataset. The proposed function achieved 99.8% accuracy and lower the loss average of 0.10692. The proposed system is further improved by utilizing various kinds of brain dataset with multi-spectral images and large set of data images.

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