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ORIGINAL ARTICLE

An Enhanced Brain Tumor Classification using Enhanced Squeeze and Excitation Network with Long Short-Term Memory

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ABSTRACT
Brain tumour classification in magnetic resonance imaging (MRI) is helpful for diagnostics, growth rate prediction, tumour volume measurements and treatment planning of brain tumour. The classification of brain tumours is performed by biopsy, which is not usually conducted before definitive brain surgery. The improvement of technology and machine learning can help radiologists in tumour diagnostics without invasive measures. A machine-learning algorithm that has achieved substantial results in image segmentation and classification is the Convolutional Neural Network (CNN). This paper developed an Enhanced Squeeze and Excitation network with LSTM (Long Short Term Memory), which combines CNN strategy to solve the optimization problem during high dimensional data classification. The proposed SE-LSTM approach it can work with large volumes of high dimensional dataset for discovering the tumours. The experimental results shown that the proposed SE-LSTM performance to improve 20% especial in terms of Accuracy compared with other existing Genetic Algorithm (GA-CNN) and Deep Learning algorithms.
Keywords: *Brain tumour, convolutional neural network, LSTM, deep learning, MRI.*

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INTRODUCTION

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.

Brain tumor is one of the deadliest diseases human have ever faced, here are some numbers to understand the impact of brain tumor on patients' lives. Less than 20% of brain tumor patients survive beyond five years of their diagnosis, whereas 86% of breast cancer and 51% of leukemia patients survive beyond five years. [1]

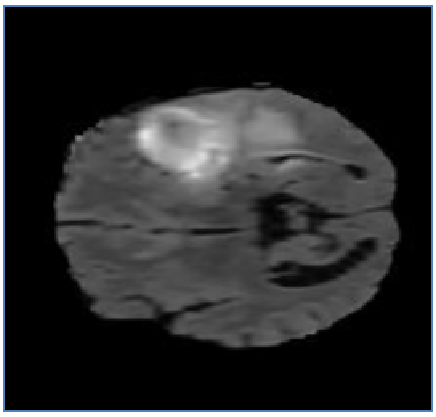

Fig. 1:Brain MRI image

In Figure 1 shows an MRI image of the brain tumor. MRI imaging technology depends on the fact that different tissues under the same magnetic field exhibit different behaviors when exposed to radio wave. Tumor segmentation is a primary step in the treatment plan of any tumor. It facilitates the surgical intervention of surgeons and the use of chemical treatment in some cases.

Deep learning [2] has been successful in computer vision, natural language processing and speech recognition. Convolutional networks [3], also known as convolutional neural networks (CNNs), are a special kind of neural network for processing data that has grid-like topology, e.g., image data, which can be thought of as a 2D grid of pixels. CNNs have achieved the state-of-the-art performance in various computer vision applications, including image recognition [4], semantic segmentation [5], object detection [6], stereo matching [7], etc. Convolutional neural networks use a linear operation called convolution and are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

Convolutional neural networks are very similar to ordinary neural networks and are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product operation and optionally follows it with a non-linearity activation function. The entire neural network still represents a single differentiable function, i.e., from the raw in-put image pixels on one end to class scores at the other. Also, they still have a loss function (e.g. cross entropy) on the last layer. All the approaches that are developed for learning general neural networks parameters still apply to CNNs. CNN architectures make the explicit assumption that the inputs of the networks are images, which allows us to incorporate certain properties into the architecture.

For traditional neural network layers, every output unit interacts with every input unit, as shown in Figure 2. However, convolutional neural networks typically have sparse interactions between input and output units, also referred to as sparse connectivity, which is achieved by setting the kernel size of CNNs smaller than the input size, as shown in Figure 3.

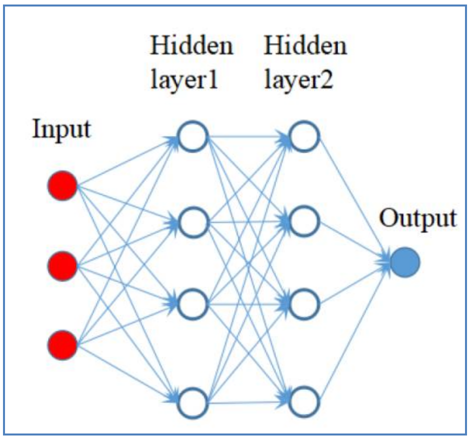

Fig. 2: Examples of fully connected neural networks

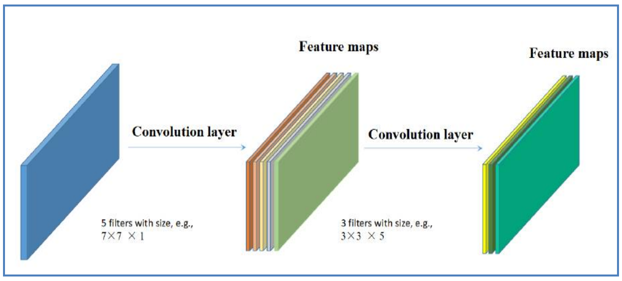

Fig. 3: Examples of convolutional networks by applying a series of filters with size smaller than the input size.

Brain tumor segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

In this paper, presents an automated brain tumor classification, a novel approach is proposed based on enhanced squeeze and excitation network with long short-term memory (LSTM) model using magnetic resonance images (MRI).

MATERIAL AND METHODS

This paper presents a novel Enhanced Squeeze and Excitation network with LSTM (Long Short Term Memory) modelinMATLAB simulation is applied to the brain image dataset. This overall proposed flow diagram in figure 3 follows a Brain tumor classification procedure form start to end state.

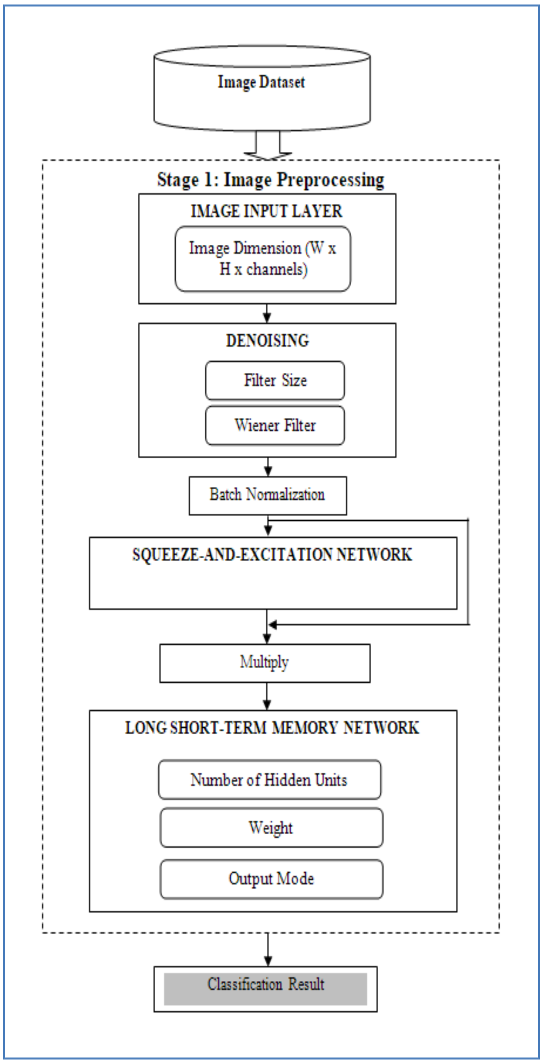

Fig.3: Proposed Flow diagram

DATA PREPROCESSING

To perform a minimal amount of preprocessing and some label-preserving transformations on the images prior to training or prediction, mostly following the method used,
Image Resizing: All images are resized to 256 pixels' minimum dimension using 'bicubic' method. Further, pixel values are converted from the integer range {0, ..., 255} to the [0, 1] single precision floating point range by dividing them by 255, to avoid possible feature scaling issues when training the network.

- Image denosing: Removing unwanted noise in order to restore the original image using Wiener filter.
- Random crops: The algorithm requires images of fixed dimensions; each time an image is picked during training to choose a random crop of the image of sized 256 by 256 pixels. This makes the size of input s fixed at training time, allowing much more efficient processing of mini-batches on the GPU. It also helps against over-fitting.

The predictable data preprocessing technique is responding as it creates with data that is unspecified prepared for examination and there is no feedback and communicates for the method of data collection. The data variation among data sets is the major difficulty for the data preprocessing. In data preprocessing, clear out customs work to uncontaminated the data by satisfying in absent values, smoothing noisy data, recognizing or discarding outliers, and determining irregularities. The real procedure of data cleansing might occupy removing typographical errors or authenticating and accurating values against a known list of entities.

NETWORK ARCHITECTURE

The network architecture is composed of a series of layers, where each layer defines a specific computation. The Deep Learning provides functionality to easily design a Neural Network layer-by-layer. The following types of layers:

- **Image Input Layer -** Image input layer (The input layer defines the type and size of data the Network can process)
- **Convolution 2d Layer -** 2D convolution layer for Convolutional Neural Networks (This layers define sets of filter weights, which are updated during network training)
- **RelU Layer -** Rectified linear unit (ReLU) layer (This layer adds non-linearity to the network, which allow the network to approximate non-linear functions that map image pixels to the semantic content of the image)
- **Max Pooling 2d Layer -** Max pooling layer (This layers downsample data as it flows through the network. In a network with lots of layers, pooling layers should be used sparingly to avoid down sampling the data too early in the network)
- **Fully Connected Layer -** Fully connected layer (This layer can be used to measure whether the input image belongs to one category or another. This measurement is made using the subsequent loss layers)
- **Softmax Layer and classification Layer -** Softmax layer (The final layers use the output of the fully connected layer to compute the categorical probability distribution over the image classes)

SQUEEZE-AND-EXCITATION (SE) NETWORK

Squeeze-and-Excitation Networks (SENets) introduce a building block for CNNs that improves channel interdependencies at almost no computational cost. The proposed SE block to acquire more accurate information which represents each channel with more points rather than only one point.

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Squeeze: Global Information Embedding

- Aggregate feature maps through spatial dimensions using global average pooling
- Generate channel-wise statistics

Excitation: Adaptive Recalibration

- Learn a nonlinear and non-mutually-exclusive relationship between channels
- Employ a self-gating mechanism with sigmoid function

✓ Input: channel-wise statistics
✓ Bottleneck configuration with two Fully Connected (FC) layers around non-linearity
✓ Output: channel-wise activations

LONG SHORT-TERM MEMORY NETWORK

- Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning.
- LSTM network are a sequence input layer and an LSTM layer. A sequence input layer inputs sequence data into the network.
- An LSTM layer learns long-term dependencies between time steps of sequence data.
- The network starts with a SE network followed by an LSTM layer. To predict class labels, the network ends with a fully connected layer, a softmax layer, and a classification output layer.

RESULTS AND DISCUSSIONS

The proposed developed an Enhanced Squeeze and Excitation network with LSTM (Long Short Term Memory) model algorithm and evaluate the performance of accuracy measures in Brain Tumor dataset in MATLAB simulation with Intel I5-6500 series 3.20 GHz 4 core processor, 8GB main memory, and runs on the Windows operating system. In this research, we will look at how the classification of applied machine learning can be used in the decision-making process. The quick and fast decision-making strategy is to pursue our experience in similar situations. ROC curve is a diagnosis model for grouping of instance between different classes. The diagnosis output is the continuous output (real value). The classifier having different boundaries between different classes can be classified by threshold value. The binary classification system is having two classes, one normal cell class which is labelled as positive (P) and other one is abnormal cell class and it is labelled as negative (N). The binary classifier has four possible outcomes

1. True Positive (TP)
2. False Positive (FP)
3. True Negative (TN)
4. False Negative (FN)

Tab1 True positive and negative values

		Training Image	
		P	**N**
Testing Image	P	TP	FN
	N	FP	TN

$$Senstivity = \frac{TP}{(TP+FN)}$$

$$Specificity = \frac{TN}{TN+FP}$$

Results from previous literatures that have used the same brain tumor types with different architecture, hyper-parameters and depths are summarized in Table 2.

$$Accuracy = \frac{True\ Positive + Ture\ Negative}{Positive + Negative}\ eqn.(1)$$

Table 2: Comparison of Accuracy (%) with existing GA-CNN, Deep Learning and proposed SELSTM

Methods	**Study I**	**Study II**
GA-CNN	**94.2**	**90.9**
Deep Learning	**96.13**	**98.7**
Proposed SELSTM	**98.6**	**99.23**

CONCLUSION

In this paper designed and implemented an enhanced method of Squeeze and Excitation network with LSTM (Long Short Term Memory) classification algorithm for high volume Brain Tumor dataset which combines LSTM Neural network model is trained to maximize the likelihood of the tumor portions given the image. The proposed method performs train deep convolutional neural networks on the overlapping crops of whole slices of brain tumor data. Since the tumor pixels account for a very small portion in the whole slice image, segmenting tumors from the background is a highly imbalanced dense prediction task.

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