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MRI Brain Images Classification Using Convolutional Neural Networks

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ABSTRACT: The purpose of this paper is to build an automatic system for extraction and Classification of brain tumor in medical images. The system is able to process Resonance Magnetic Images (MRI) most quickly with a high detection rate. Indeed, based on Convolutional Neural Network (CNN) method for Classification and a thresholding algorithm for image segmentation, the system has been developed. Moreover, many experiments were conducted to evaluate the performance of our approach using different optimizers with a huge dataset of MRI brain images. Results showed that the Root Mean Square Propagation (RMSprop) optimizer converges faster with a highest accuracy comparing to other optimizers.

KEYWORDS: Classification, Convolutional Neural Networks, Deep learning, Resonance Magnetic Images, Big data.

I. INTRODUCTION

According to statistics from the World Health Organization, Cancer is the second leading cause of death in the world. Detecting cancer at an advanced stage and the lack of access to diagnosis and treatment are common problems that increase the rate of deaths. For this reason, a Classification tool for medical images, especially the detection of brain tumors is very important. But, due to the huge amount of information coming from hospitals, especially medical images, it becomes so hard to classify every image manually and to store it into its appropriate folder to track the diseases of each subject. The new challenge now is how to build an automatic system that can classify and store images without human intervention. Otherwise, deep learning has demonstrated its superior performance on a wide variety of tasks including speech, natural language, and images. It has become the go-to technique for most Artificial Intelligence (AI) type problems, because its capacity to deal with big data, particularly to extract features and to classify medical images in order to store them in a distributed database.

Past work on image recognition has emerged strongly either using classical or modern methods often derived from machine learning algorithms. Several researches had been done in object detection in image and video processing based on traditional techniques by using Content-Based Image Retrieval and Classification techniques, or on advanced techniques such as AI. Authors in [1] proposed a method that combines digital image processing and a thresholding method for a segmentation algorithm. In [2], Hu uses a feature extractor based on mathematical morphology and the powerful machine learning model Support Vector Machine (SVM). The work of Nelly Gordillo *et al.* in [3] presents a state of the art survey on MRI brain tumor segmentation. In this work, the authors enumerate manual and automated segmentation approaches. They list the most relevant existing techniques for the segmentation of brain tumors such as thresholding, watershed, region-based techniques, and pixel Classification techniques. A new approach was proposed by Dimitrovski *et al.* in [4] where they used, among others, a standard Classification of Medical Images using Convolutional Neural Networks. Their experiments offer a complete representation of the visual content in an image. Another research in this field is the study of Erickson *et al.* in [5]. The objective of their work is to detect tumors using machine learning, such as SVM and K-Nearest Neighbors (K-NN), and they made a comparative study between traditional machine learning and deep learning. In [6], Affonso *et al.* used deep learning, especially CNN, with a combination of texture-based feature extraction techniques and traditional techniques. This work was relayed on Haralick's texture descriptors [7] to pre-process an image before training a model by different machine learning techniques. In the same context, Tanga *et al.*, in [8], used the multiscale Sparse Auto Encoders (SAEs) Networks from [9], which are the most popular representations of unsupervised learning methods to extract image features. Mohan and Subashini proposed a study of medical image Classification using MRI format [10]. In their work, they retrospect the

current trends in segmentation and Classification relevant to tumor infected human brain MR images. They give a list of techniques used to pre-process images before classifying them, and some segmentation approaches such as manual, semi-automatic and fully automatic segmentation. Descombes *et al.* presented a new approach for segmenting 3D tomographic vascular network images into pathological and normal regions from considering their micro-vessel 3D structure only [11, 12]. They define and use a conditional random field for segmenting the output of a watershed algorithm. The tumoral and normal classes are thus characterized by their respective distribution of watershed region size interpreted as local vascular territories. El-Boustani *et al.* used different neural networks architectures to compress MRI brain images [13]. More recently, Kheradpisheh *et al.* have shown that spike-timing- dependent plasticity (STDP) can be used in spiking neural networks (SNN) to extract visual features of low or intermediate complexity in an unsupervised manner [14].

From this state-of-the-art, we noticed that basic image processing feature extraction and Classification schemes are much easier to implement and are computationally less expensive; however, the modern techniques based on deep learning gives better performance, especially when dealing with huge amount of data. This motivated our research for building an automatic system by combining preprocessing techniques, a more sophisticated CNN, and a SVM decision model to improve the results. While most of the previously cited studies used only one trainable layer, we propose in this paper to design a deep CNN comprising several convolutional and pooling layers. We evaluate the proposed scheme on MRI brain images, generated by the National Cancer Institute Clinical Proteomic Tumor Analysis Consortium (CPTAC), using different optimizer functions.

The paper is structured as follows. In the next section, we present our proposed approach and the different tools used in our study. In Sect. 3, we present the used data and the design of our experiments. Section 4 sets out our key experimental results, including some statistical analysis and interpretations and a comparative study. And in Sect. 5, we state some concluding remarks and suggestions for future work.

II. THE PROPOSED APPROACH

To build our system, two main steps are necessary. The first step revolves around the construction of a model using a training set where some medical images are chosen to extract the image features. The second step depends on medical images dataset to be classified. Images from this dataset will be processed by the system to extract its features and, based on the output data, the system determinates to which class an image will belong. Figure 1 describes the process chosen to extract and classify medical images.

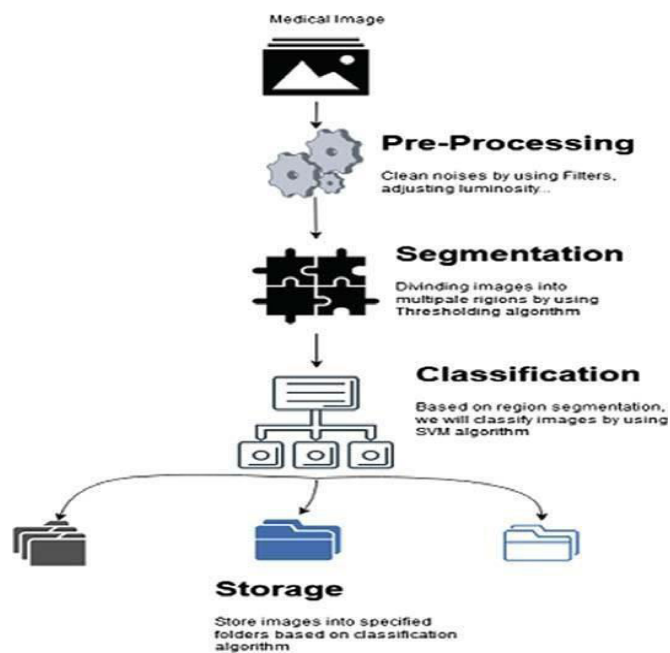


Fig. 1. The step-by-step Classification processes

2.1 Image Pre-processing

We start with cleaning the images. As it's known, image in general contains two kinds of information: useful and un-useful information. So it's obvious that we need some methods that can remove useless information and keep just useful ones. Before the recognition step, we have to do many pre-processing treatments such as *filtering* the images, cleaning noises and adjusting luminosity, etc. Sometimes, we use morpho- logical operators like closing with a ball as a structuring element to repair the image structure. This part can help us to obtain good results and thus build a good model.

2.2 Thresholding Algorithm

In this paper, we adapted a thresholding algorithm to segment images and extract regions that we need to build our model. Thresholding is an algorithm which trans- forms images to binary images (0 or 1) based on a threshold value T , which helps to segment images to uniform regions. Figure 2 shows the result of the thresholding algorithm for a MR brain image.

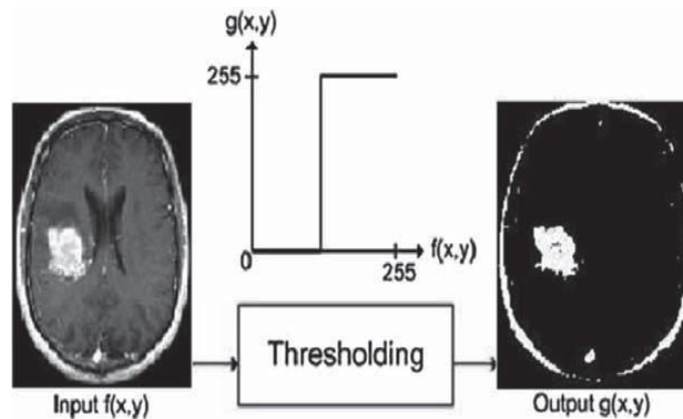


Fig. 2. Thresholding of an MRI Brain image

2.3 Convolutional Neural Networks

Deep learning models have achieved remarkable results in computer vision, so they become a new tendency in image recognition and Classification. In this context appears our used CNN algorithm. As we can see from Fig. 3, the CNN is divided into 4 steps which are Convolution, Non Linearity (ReLU), Pooling or Sub- Sampling and Classification (Fully Connected Layer). These operations are crucial to build a CNN system.

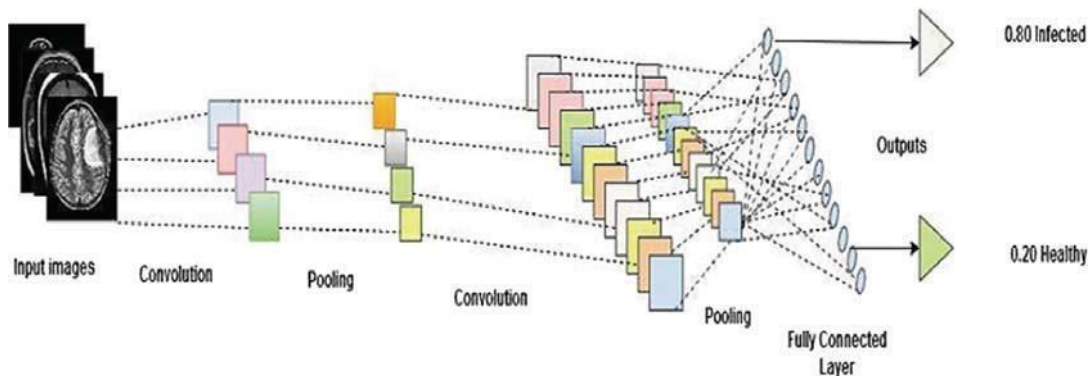


Fig. 3. CNN architecture with 2 convolution and pooling layers

III. EXPERIMENTS

Our dataset of brain images is composed with samples from two classes, healthy brain and brain with Tumor. This dataset was downloaded from Kaggle (Platform for pre- dictive modeling and analytics competitions) and from the Cancer Imaging Archive (TCIA) generated by the National Cancer Institute Clinical Proteomic Tumor Analysis Consortium (CPTAC) [15]. We choose 1000 axial MRI images in our test as it is shown in Fig. 4 below.

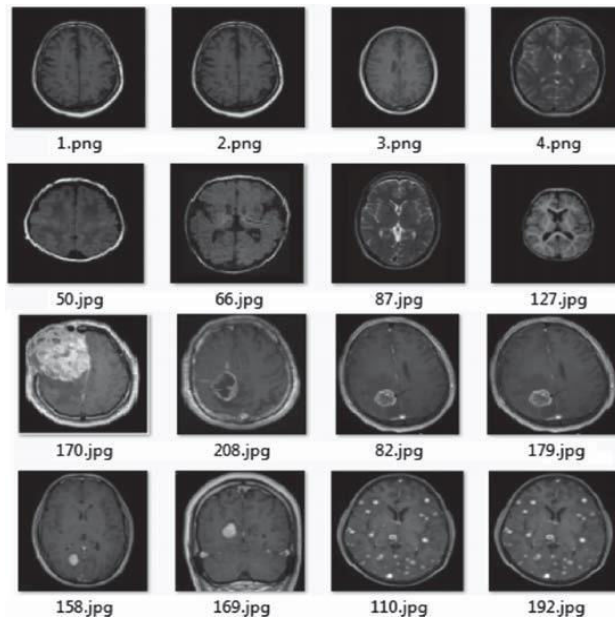


Fig. 4. Examples of MRI Brain images: Healthy (left) and Diseased (right)

As it's mentioned before, we pre-process images before the recognition step to eliminate noising areas using Gaussian filter, then we use Thresholding algorithm to remove areas that do not provide useful information for our system (Fig. 5). The MRI brain images are pretty good contrasted and easy to binarize so that we settled the threshold, most of the time, to the half of the image dynamic, i.e. the maximum gray level.

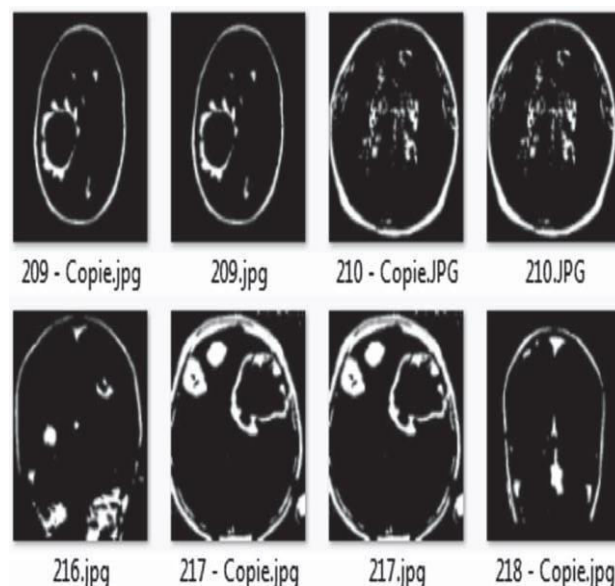


Fig. 5. Image segmentation using thresholding



We have to mention that our experiments were conducted on HP computer with i3 core processors. Our program is developed using Python Programming Language, and using Keras and Tensorflow Libraries which are dedicated to the CNN programming. Figure 8 presents the interface of the developed software using our proposed approach. After the preprocessing step, our CNN extracts features using the four steps as mentioned before. To compute the loss, we implemented the support vector machine (SVM) instead of the conventional softmax function with the cross entropy function. The SVM objective is to find the optimal hyperplane to separate two classes in a given dataset. The weight parameters are then learned using three different optimizer functions: Stochastic Gradient Descent (SGD), Adaptive Moment Optimization (Adam) and Root Mean Square Propagation (RMSprop). These optimizers perform a parameter update for each training example. The following section presents and discusses the obtained results of our approach.

IV. RESULTS AND DISCUSSION

Figure 6 shows the training accuracy and loss of CNN-SVM when epoch is fixed on 30, while Fig. 7 shows accuracy and loss for epoch = 50. In this test, we used the RMSprop optimizer [16] and mean squared error distance. Notice that in every test, we change the number of epochs when an entire dataset is passed forward and backward through the network.

We can notice clearly that the learning rate increases and the value lost decreases steadily and faster when the number of epochs increases. This is because increasing the epoch's number implies weights updating in the neural network. Thus, as much as we train the network, it would memorize the desired outputs for the training set inputs.

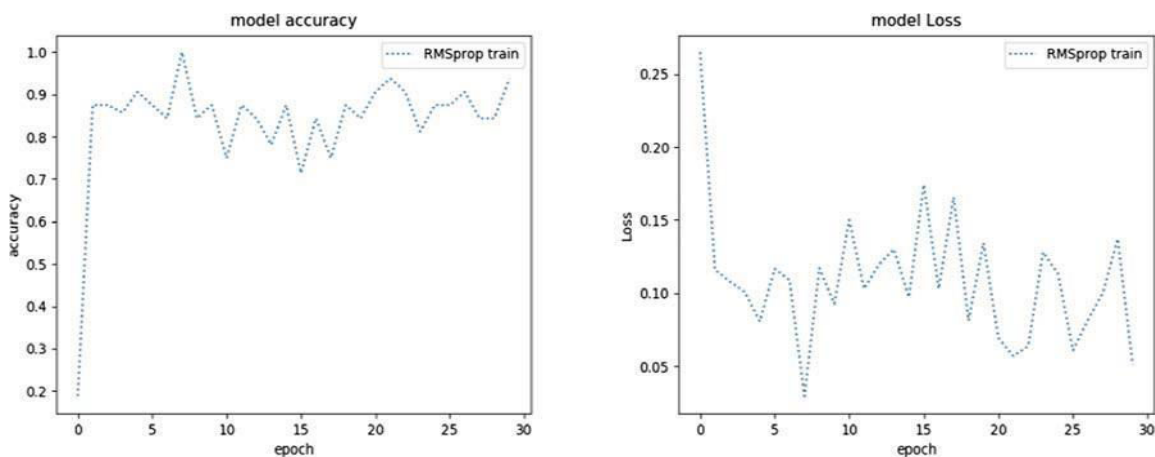


Fig. 6. Accuracy and loss versus epochs (=30)

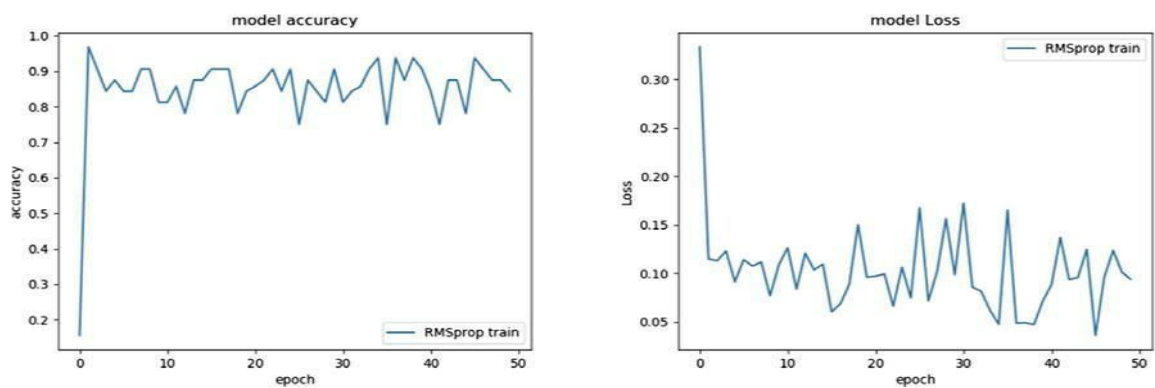


Fig. 7. Accuracy and loss vs epochs (=50)



Figure 8 shows the execution time for every epoch of our program. As we can see, as much as we increase epoch number, which is the number of iterations, the execution time becomes higher and higher. In this figure, we can notice that the execution time can be almost represented by an increasing linear function. There are some exceptions which are represented by red dots. These abrupt changes in the execution time are due to the machine performance. It is well known that the CNN needs higher material performances to product results in a minimal time. In normal case, we use GPU to compile this kind of programs.

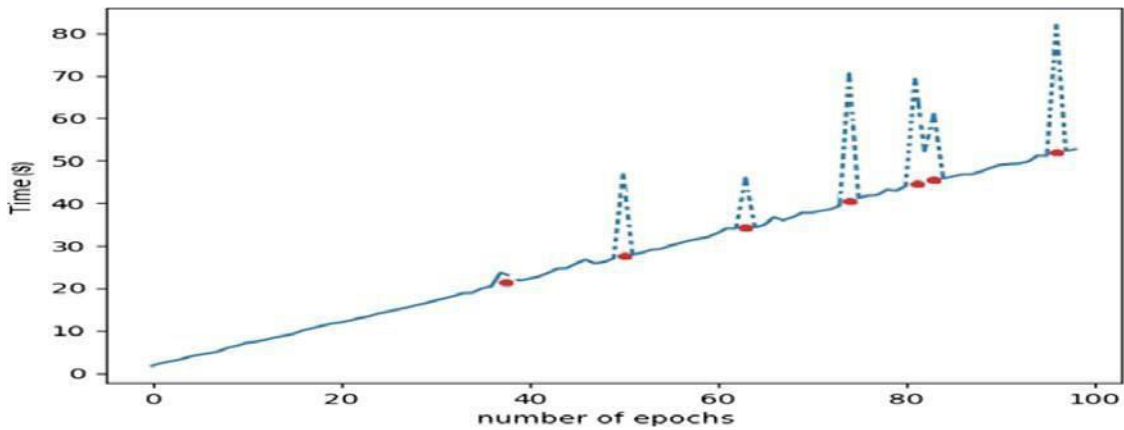


Fig. 8. Execution time versus number of epochs

Table 1 shows results obtained using the 3 optimizer’s functions, Adam, SGD [17]and RMSprop.

Table 1. Accuracy, loss and the execution time for SGD, Adam and RMSprop

Optimizer	Accuracy	Loss	Execution time (S)
epoch = 40			
Adam	0.8125	0.131	20.7012
RMSprop	0.837	0.11	20.1084
SGD	0.874	0.126	19.6258
epoch = 80			
Adam	0.875	0.0996	39.0468
RMSprop	0.932	0.071	38.532
SGD	0.9.68	0.049	38.3302
epoch = 100			
Adam	0.876	0.107	58.2037
RMSprop	0.906	0.0071	57.7669
SGD	0.901	0.099	58.0477

We can remark from the table that Adam optimizer did not undergo a big change in accuracy and loss, and compared to the 2 others, its execution time is the highest one. The most stable function is the RMSprop optimizer. As more as we increase the number of epochs, the precision keeps increasing and the execution time is the lowest compared to the other functions, which justifies the use of this function in our research.

It is clear that RMSprop optimizer gives the best performance compared with the other functions. The accuracy with this function reaches sometimes 0.98 and it represents the highest value reached by the 3 functions for the same sample.

We can clearly see that the loss decreases proportionally in every epoch with Adam, RMSprop and SGD optimizers. It also shows that RMSprop and SGD optimizers minimize the loss and perform better. We can summarize that RMSprop performs better than the other optimizers in this type of images (MRI brain images) according to the accuracy, the loss and especially the execution time. The obtained results are in line with the research of Saikat Roy *et al.* [18]. RMSprop performs better than the 2 other functions and converges to equivalent accuracies even at lower number of iterations.

V. CONCLUSION AND FUTURE WORK

We have presented in this paper an automatic system to classify MRI brain images. We developed and implemented an algorithm based on adapted CNN, and showed that this method permits to classify tumorous and normal brain image with an accuracy of almost 98%. The results are very sound and can be very helpful for physicians and/or medical staff to make medical decisions. Despite the material limitation and the size of dataset, the system works well and outperforms some related studies. We have shown that the RMSprop performs better than the other optimizers for MRI brain images, according to the accuracy, the loss and especially the execution time. Furthermore, the Classification process has been done in the big data context. The challenges faced in this work, is to select the best existing classifier especially in a huge brain tumor dataset. In future work, we can extend this Classification to a large number of classes and generalize the program to be applicable on 3D MRI images which is a big challenge since there are lacks of data. More importance must be given to the pre-processing step as this part can help us to build a stronger model and thus to obtain better results.

REFERENCES

1. McCulloch, W.S., Pitts, W.: A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.* 5, 115–133 (1943)
2. Hu, M.K.: Visual pattern recognition by moment invariant. *IRE Trans. Inf. Theory* 8, 179–187 (1962)
3. Gordillo, N., Montseny, E., Sobrevilla, P.: State of the art survey on MRI brain tumor segmentation. Elsevier (2013)
4. Dimitrovski, I., Kocov, D., Kitanovski, I., Loskovska, S., Dzeroski, S.: Improved medical image modality Classification using a combination of visual and textual features. Elsevier (2014)
5. Erickson, B.J., Korfiatis, P., Akkus, Z., Kline, T.L.: Machine learning for medical imaging. In: *RSNA Annual Meeting*, November 2016
6. Affonso, C., Rossi, A.L., Vieira, F., Carvalho, A.: Deep learning for biological image Classification. Elsevier, June 2017
7. Haralick, R., Shanmugam, K., Dinstein, I.: Textural features for image Classification. *IEEE Trans.* (1973)
8. Tang, Q., Liu, Y., Liu, H.: Medical image Classification via multiscale representation learning. Elsevier, June 2017
9. Le, Q.V.: Building high-level features using large scale unsupervised learning. Google Inc., USA, June 2012
10. Mohan, G., Subashini, M.: MRI based medical image analysis: survey on brain tumor grade Classification. Elsevier (2017)
11. Descombes, X., Plouraboué, F., El Boustani, A., Fonta, C., Le Duc, G., Serduc, R., Weitkamp, T.: Vascular network segmentation: an unsupervised approach. In: *IEEE 9th International Symposium of Biomedical Imaging (ISBI)*, pp. 1248–1251 (2012)
12. Descombes, X., Plouraboué, F., El Boustani, A., Fonta, C., Le Duc, G., Serduc, R., Weitkamp, T.: Brain tumor vascular network segmentation from micro-tomography. In: *IEEE 8th International Symposium of Biomedical Imaging (ISBI)*, pp. 1113–1116 (2011)
13. El Boustani, A., Kinsner, W.: Selective compression of MRI brain images using two classes of neural networks. In: *Proceedings of the International Conference on Image and Signal Processing, ICISP 2001*, vol. 1, no. 2, pp. 216–220 (2001)
14. (2001)
15. Kheradpisheh, S.R., Ganjtabesh, M., Thorpe, S.J., Masquelier, T.: STDP-based spiking deep convolutional neural networks for object recognition. *Neural Netw.* 99, 56–67 (2017)
16. Clark, K., Vendt, B., Smith, K., Freymann, J., Kirby, J., Koppel, P., Moore, S., Phillips, S., Maffitt, D., Pringle, M., Tarbox, L., Prior, F.: The Cancer Imaging Archive (TCIA): maintaining and operating a public information repository. *J. Digit. Imaging* 26(6), 1045–1057 (2013)
17. Mukkamala, M.C., Hein, M.: Variants of RMSProp and adagrad with logarithmic regret bounds. In: *International Conference on Machine Learning, Sydney, Australia* (2017)
18. Roy, S., Das, N., Kundu, M., Nasipuri, M.: Handwritten isolated Bangla compound character recognition: a new benchmark using a novel deep learning approach. *Pattern Recognit. Lett.* 90, 15–21 (2017)



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