Deep Learning Applications in Medical Image Analysis on Brain Tumor

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Abstract—Machine learning algorithms have the potential to be invested deeply in all fields of medicine, from drug discovery to clinical decision making, significantly altering the way medicine is practiced. In existing work, medical images are an integral part of a patient's EHR and are currently analyzed by human radiologists, who are limited by speed, fatigue, and experience. Therefore, it is ideal for medical image analysis to be carried out by an automated, accurate and efficient machine learning algorithm. Yet the situation may not be as dire as it seems, as despite the small training datasets, the papers in this review report relatively satisfactory performance in the various tasks. In proposed work, in medical image analysis is an active field of research for machine learning, partly because the data is relatively structured and labelled, and it is likely that this will be the area where patients first interact with functioning, practical artificial intelligence systems. Firstly, in terms of actual patient metrics, medical image analysis is a litmus test as to whether artificial intelligence systems will actually improve patient outcomes and survival. Secondly, it provides a testbed for human-AI interaction, of how receptive patients will be towards health-altering choices being made, or assisted by a nonhuman actor. In medical image analysis, the lack of data is two-fold and more acute. Most of the datasets presented in this review involve fewer than 100 patients. The question of how many images is necessary for training in medical image analysis was partially answered by ascertained the accuracy of a CNN with GoogleNet architecture in classifying individual axial CT images into one of 6 body regions: brain, neck, shoulder, chest, abdomen, pelvis. With 200 training images, accuracies of test were achieved on a test set of 6000 images. An important, non-technical challenge is the public reception towards their health results being studied by a nonhuman actor.

Index Terms-- Image detection, Image classification, Machine learning, Image pre-processing techniques, Classifiers (SVM, LG, CNN), Python, Modules or Libraries.

I. INTRODUCTION

The tremendous success of machine learning algorithms at image recognition tasks in recent years intersects with a time of dramatically increased use of electronic medical records and diagnostic imaging. This review introduces machine learning algorithms as applied to medical image analysis, focusing on convolutional neural networks, and emphasizing clinical aspects of the field. The advantage of machine learning in an era of medical big data is that significant hierarchal relationships within the data can be discovered algorithmically without laborious hand-crafting of features. We cover key research areas and applications of medical image classification, localization, detection, segmentation and registration. We conclude by discussing research obstacles, emerging trends and possible future directions. Medical image analysis is an active field of research for machine learning, partly because the data is relatively structured and labelled, and it is likely that this will be the area where patients first interact with functioning, practical artificial intelligence systems. This is significant for two reasons. Firstly, in terms of actual patient metrics, medical image analysis is a litmus test as to whether artificial intelligence systems will actually improve patient outcomes and survival. Secondly, it provides a testbed for human-AI interaction, of how receptive patients will be towards health-altering choices being made, or assisted by a non-human actor

II. EXISTING SYSTEM

Parveen, Amritpal Singh [2] purposed algorithm is a combination of SVM and fuzzy c- means, a hybrid technique for prediction of brain tumor. Here, the image is enhanced using contrast improvement, and mid-range stretch. Double thresholding and morphological operations are used for skull striping. Fuzzy c- means (FCM) clustering is used for the image segmentation. Grey level run length matrix (GLRLM) is used for extraction of feature. Another existing method Numerous brain diagnostic systems have been developed using classical ML algorithms including Random Forests (RFs), k-Nearest

Neighbor (k-NN), to list a few. These algorithms are used alone or in combination with other ML algorithms or feature selection techniques.

Disadvantages

- It is not possible to detect disease without consultation of doctor.
- It will take more time to calculate our dataset which we having our Brain Tumor dataset.
- Discover patterns using traditional data mining tools may not use for predictions.
- Information can be lost or manipulated in records easily.
- Previous applications were not 100 percent accurate and this leads to in accurate information of disease.

III. PROPOSED SYSTEM

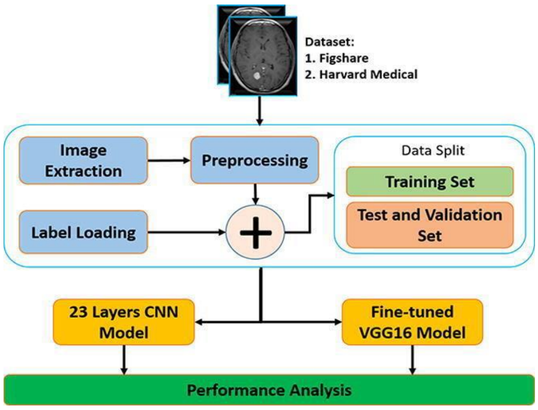
This project is aimed at developing an application called Brain Tumor Detection system based on MRI dataset. Magnetic resonance imaging (MRI) is the most useful imaging tool in the evaluation of patients with brain tumors. A deep learning based technique (Convolutional Neural Network) was proposed in this model. The proposed Convolutional Neural Network (CNN) model was being tested using different image segmentation methods and different datasets. Finally, the best image segmentation method obtained a high accuracy of around 96%. Results of those experiments suggest an important role for the early diagnosis of Brain tumor using image processing and deep learning techniques. Our application is 96 percent accurate and it is fast, robust, reliable and easy to use.

After examining many algorithms for detecting brain tumors, we found that most algorithms required a long computational time, while cheap computational time methods could not provide great accuracy. Another downside is that scaling up the process is nearly impossible because each estimator is based on the accuracy of preceding predictors. As a result, we intended to propose an approach that could provide excellent accuracy.

Advantages

- It helps patient to detect and find stage of Brain Tumor easily.
- Minimal time, cost and effort spent.
- Discover patterns using machine learning algorithm that identify the best mode of treatment for Tumor across different age.
- This application can recognize different MRI images with high accuracy.

IV. SYSTEM ARCHITECTURE



A) Dataset Processing

For training and testing the model, 'Brain Tumor Dataset' which consist of 3064 brain scanned image slices are taken from 233. All three kinds of brain tumors: Meningioma, Glioma, and Pituitary, respectively. Total images for each category of tumor is: 708 images for Meningioma, 1426 images for Glioma and 930 images for Pituitary tumor [7][9]

B) Pre-processing

In MR imaging technique, specific image appearances are given by setting some parameters such as radio frequency pulses and gradients.[1][2] T1 and T2 are the most common MRI sequences, and each provides particular details about tissues that occurred in brain. T1 images are being in this study, for normal cases. In order to reduce the number of normal brain images, there are six sections with approximately equal intervals have been selected from MR images of each normal person. In the gadolinium enhanced T1 MR images, due to the injection of a contrast agent called Gadolinium, tumor boundaries can be better identified [8].

C) CNN Training

CNN Convolutional Neural Network (ConvNet or CNN) well known neural network for specially image recognition and classification. CNN is highly excellent in extracting complex features for classifications. CNN consist of neurons where weight and bias can be learned. Each neuron receives some input; weighted sum is taken then given to the activation function. CNN uses successive convolution layer and nonlinear ReLU function to extract valuable feature with specific dimension.[3][4] Maxpooling layer is used to downsize the feature map. In Fully connected layer, each neuron is connected to every other neuron of previous dense layer. Back- propagation and gradient descent are used while training the network. Softmax function is probability distribution to limit all class output value between 0 and 1. CNN provides feature maps which helps neural network to learn small features of the image depending on the depth of hidden layers[11][12].

D) SVM Classification

SVM Support vector classifier is a supervised learning algorithm that works on the feature matrix taken from the input images, recognize the patterns and finally find the maximum separated hyperplane three types of tumor.

V. SAMPLE SCREENS

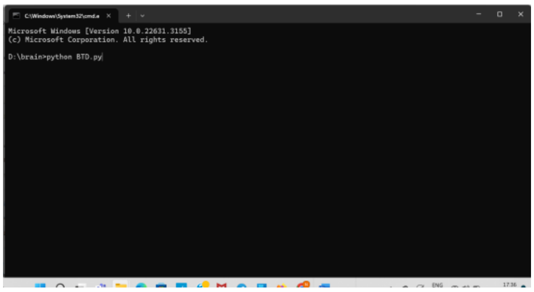


Fig: Run project

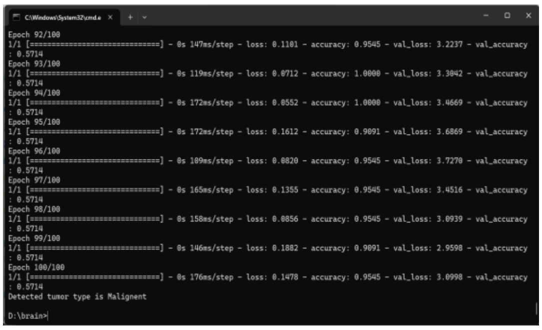


Fig: Trained Dataset

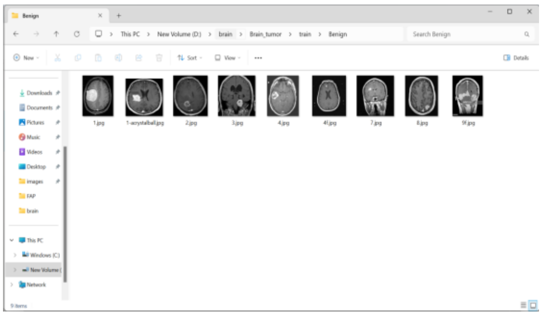


Fig: Trained Datasets with images

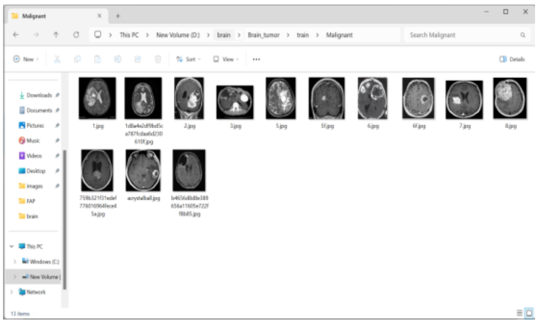


Fig: select a image and predict

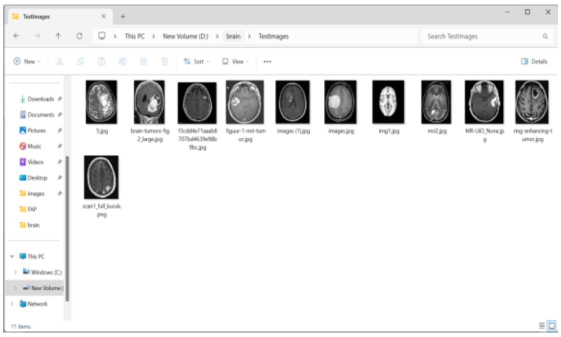


Fig : Predicted Tumor

CONCLUSION

A recurring theme in machine learning is the limit imposed by the lack of labelled datasets, which hampers training and task performance. Conversely, it is acknowledged that more data improves performance, as Sun et al. [85] shows using an internal Google dataset of 300 million images. In general computer vision tasks, attempts have been made to circumvent limited data by using smaller filters on deeper layers [47], with novel CNN architecture combinations [86], or hyperparameter optimization [87]. In medical image analysis, the lack of data is two-fold and more acute: there is general lack of publicly available data, and high quality labelled data is even more scarce. Most of the datasets presented in this review involve fewer than 100 patients. Yet the situation may not be as dire as it seems, as despite the small training datasets, the papers in this review report relatively satisfactory performance in the various tasks. The question of how many images are necessary for training in medical image analysis was partially answered by Cho et al. [88]. He ascertained the accuracy of a CNN with GoogLeNet architecture in classifying individual axial CT images into one of 6 body regions: brain, neck, shoulder, chest, abdomen, pelvis. With 200 training images, accuracies of 88-98% were achieved on a test set of 6000 images.

REFERENCES

[1] C.-J. Hsiao, E. Hing, and J. Ashman, ''Trends in electronic health record system use among office-based physicians: United states, 2007–2012,'' Nat. Health Stat. Rep., vol. 75, pp. 1–18, May 2014.

[2] R. Smith-Bindman et al., ''Use of diagnostic imaging studies and associated radiation exposure for patients enrolled in large integrated health care systems, 1996–2010,'' JAMA, vol. 307, no. 22, pp. 2400–2409, 2012.

[3] E. H. Shortliffe, Computer-Based Medical Consultations: MYCIN, vol. 2. New York, NY, USA: Elsevier, 1976.

[4] G. Litjens et al. (Jun. 2017). ''A survey on deep learning in medical image analysis.'' [Online]. Available: https://arxiv.org/abs/1702.05747

[5] W. S. McCulloch and W. Pitts, ''A logical calculus of the ideas immanent in nervous activity,'' Bull. Math. Biol., vol. 5, nos. 4, pp. 115–133, 1943.

[6] F. Rosenblatt, ''The perceptron: A probabilistic model for information storage and organization in the brain,'' Psychol. Rev., vol. 65, no. 6, pp. 365–386, 1958.

[7] D. H. Hubel and T. N. Wiesel, ''Receptive fields, binocular interaction and functional architecture in the cat's visual cortex,'' J. Physiol., vol. 160, no. 1, pp. 106–154, 1962.

[8] K. Fukushima and S. Miyake, ''Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition,'' in Competition and Cooperation in Neural Nets. Berlin, Germany: Springer, 1982, pp. 267–285.

[9] Y. LeCun et al., ''Backpropagation applied to handwritten zip code recognition,'' Neural Comput., vol. 1, no. 4, pp. 541–551, 1989.

[10] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, ''Learning representations by back-propagating errors,'' Nature, vol. 323, pp. 533–536, Oct. 1986.

[11] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ''ImageNet classification with deep convolutional neural networks,'' in Proc. Adv. Neural Inf. Process. Syst., 2012, pp. 1097–1105.

[12] D. Shen, G. Wu, and H.-I. Suk, ''Deep learning in medical image analysis,'' Annu. Rev. Biomed. Eng., vol. 19, pp. 221–248, Mar. 2017.

[13] K. Suzuki, ''Overview of deep learning in medical imaging,'' Radiol. Phys. Technol., vol. 10, no. 3, pp. 257–273, 2017.

[14] H. Greenspan, B. van Ginneken, and R. M. Summers, ''Guest editorial deep learning in medical imaging: Overview and future promise of an exciting new technique,'' IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1153–1159, May 2016.

[15] D. Adams. (2017). Publish or Perish 5. Accessed: Oct. 30, 2017. [Online]. Available: https://harzing.com/resources/publish-or-perish/windows

[16] K. Clark et al., ''The cancer imaging archive (TCIA): Maintaining and operating a public information repository,'' J. Digit. Imag., vol. 26, no. 6, pp. 1045–1057, 2013.

[17] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers. (Dec. 2017). ''ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases.'' [Online]. Available: https://arxiv.org/abs/1705. 02315

[18] E. Gibson et al. (Oct. 2017). ''NiftyNet: A deep-learning platform for medical imaging.'' [Online]. Available: https://arxiv.org/abs/1709.03485

[19] O. Ronneberger, P. Fischer, and T. Brox, ''U-net: Convolutional networks for biomedical image segmentation,'' in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent., 2015, pp. 234–241.

[20] F. Milletari, N. Navab, and S.-A. Ahmadi, ''V-net: Fully convolutional neural networks for volumetric medical image segmentation,'' in Proc. 4th Int. Conf. 3D Vis. (3DV), Oct. 2016, pp. 565–57.