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AN ARTIFICIAL INTELLIGENCE ARCHITECTURAL MODEL DESIGNED TO DETECT ALZHEIMER'S-RELATED BRAIN TUMORS

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Abstract :

Alzheimer's disease stands as a prominent neurodegenerative disorder, presenting initially mild symptoms that progress to severe manifestations over time. The absence of a cure makes this ailment particularly formidable, with diagnosis typically occurring in advanced stages.. This study showcases the unexplored capabilities of the brain tumor architecture model in detecting brain tumors and adds to the expanding research on utilizing deep learning in the medical field. Given the brain's constrained space within the inflexible skull, any abnormal growth can result in serious complications, underscoring the importance of timely and precise detection for successful treatment.

Key Words:
Magnetic Resonance Imaging [MRI] , Deep Learning , Segmentation, Convolutional Neural Network, Machine Learning.

I. INTRODUCTION

Brain tumors, characterized by abnormal cell proliferation within the brain, pose a critical health challenge . As the brain is confined within the rigid skull, any undue expansion can lead to severe complications, making early and accurate detection vital .Traditionally, detection involved an expert examination of medical images, primarily magnetic resonance imaging (MRI) scans. However, this approach can be time-consuming and potentially lead to missed or incorrect diagnoses. Deep Learning (DL), a subfield of machine learning, has emerged as a powerful tool showing significant promise in various domains, notably in image recognition and analysis. DL systems have the potential to reduce human effort significantly and have revolutionized many sectors, including healthcare. However, applying DL to MRI-based brain tumor detection presents challenges and limitations. These include issues related to image quality, high degrees of anatomical variations, and the need for domain-specific expert interpretation . Overcoming these challenges is a significant factor that can dramatically influence the effectiveness and reliability of DL models and understanding these challenges is integral to the context of the current study. Figure 1 outlines the general architecture of a deep neural network.
While the potential advantages of the VGG-16 architecture in brain tumor detection are briefly mentioned in few of the earlier studies, a more detailed context about the state-of-the-art models in this field is required.

II. LITERATURE SURVEY

[1] C.-J. Hsiao, E. Hing, and J. Ashman, ``Trends in electronic health record system use among ofce-based physicians: United states, 20072012,'' Nat. Health Stat. Rep., vol. 75, pp. 118, May 2014

This report presents trends in the adoption of electronic health records (EHRs) by office-based physicians during 2007-2012. Rates of adoption are compared by selected physician and practice characteristics.Methods: The National Ambulatory Medical Care Survey (NAMCS) is based on a national probability sample of nonfederal office-based physicians who see patients in an office setting. Prior to 2008, data on physician characteristics were collected through in-person interviews with physicians. To increase the sample for analyzing physician adoption of EHR systems, starting in 2008, NAMCS physician interview data were supplemented with data from an EHR mail survey. This report presents estimates from the 2007 in-person interviews, combined 2008-2010 data from both the in-person interviews and the EHR mail surveys, and 2011-2012 data from the EHR mail surveys. Sample data were weighted to produce national estimates of office-based physician characteristics and their practices.

2. R. Smith-Bindman et al., ``Use of diagnostic imaging studies and associated radiation exposure for patients enrolled in large integrated health care systems, 19962010,'' JAMA, vol. 307, no. 22, pp. 24002409, 2012.

Results: During the 15-year study period, enrollees underwent a total of 30.9 million imaging examinations (25.8 million person-years), reflecting 1.18 tests (95% CI, 1.17-1.19) per person per year, of which 35% were for advanced diagnostic imaging (computed tomography [CT], magnetic resonance imaging [MRI], nuclear medicine, and ultrasound). Use of advanced diagnostic imaging increased from 1996 to 2010; CT examinations increased from 52 per 1000 enrollees in 1996 to 149 per 1000 in 2010, 7.8% annual increase (95% CI, 5.8%-9.8%); MRI use increased from 17 to 65 per 1000 enrollees, 10% annual growth (95% CI, 3.3%-16.5%); and ultrasound rates increased from 134 to 230 per 1000 enrollees, 3.9% annual growth (95% CI, 3.0%-4.9%). Although nuclear medicine use decreased from 32 to 21 per 1000 enrollees, 3% annual decline (95% CI, 7.7% decline to 1.3% increase), PET imaging rates increased after 2004 from 0.24 to 3.6 per 1000 enrollees, 57% annual growth. Although imaging use increased within all health systems, the adoption of different modalities for anatomic area assessment varied. Increased use of CT between 1996 and 2010 resulted in increased radiation exposure for enrollees, with a doubling in the mean per capita effective dose (1.2 mSv vs 2.3 mSv) and the proportion of enrollees who received high (>20-50 mSv) exposure (1.2% vs 2.5%) and very high (>50 mSv) annual radiation exposure (0.6% vs 1.4%). By 2010, 6.8% of enrollees who underwent imaging received high annual radiation exposure (>20-50 mSv) and 3.9% received very high annual exposure (>50 mSv).

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

Computer-Based Medical Consultations: MYCIN focuses on MYCIN, a novel computer-based expert system designed to assist physicians with clinical decisions concerning the selection of appropriate therapy for patients with infections. It discusses medical computing, artificial intelligence, and the clinical problem areas for which the MYCIN program is designed, and it describes in detail how the MYCIN program helps physicians in making decisions. Comprised of seven chapters, this volume begins with an overview of MYCIN and the criteria used in its design. It then discusses data structures and control structures in the context of prior work regarding rule-based problem-solving, inferential model building and inexact reasoning in medicine. The book also explores MYCIN'S ability to answer questions with respect to its knowledge base and the details of a specific consultation, evaluation and future extensions of the MYCIN system, the limitations and accomplishments of MYCIN, and its contributions in artificial intelligence and computer-based medical decision making. This book is a valuable source of information for computer scientists and members of the medical community.

4.Singh, A., Sharma, A., Tuli, S., & Verma, A. K. (2020). Exploring Machine Learning Applications in Alzheimer's Disease Prediction: A Comprehensive Review. Journal of Healthcare Engineering, 2020.

How does this review contribute to understanding the role of machine learning in predicting Alzheimer's disease? What specific machine learning techniques are discussed in this review, and how do they contribute to predictive modeling? What are the key findings or insights provided by the authors regarding the effectiveness of machine learning models in Alzheimer's disease prediction? How does this review address the limitations or challenges associated with current machine learning approaches in Alzheimer's disease prediction? Based on the review's findings, what are the potential implications for future research or clinical applications in Alzheimer's disease prediction using machine learning algorithms?

5. Li, Y., Zheng, S., & Xu, Y. (2019). Utilizing 3D Convolutional Neural Networks for Alzheimer's Disease Prediction: A Neuroimaging Investigation. Frontiers in Neuroscience, 13, 797.

How do convolutional neural networks contribute to the prediction of Alzheimer's disease, as discussed in this neuroimaging study?
What are the primary findings or results obtained from the application of 3D convolutional neural networks for Alzheimer's disease prediction?
How does this study address the potential advantages or limitations of using neuroimaging data and deep learning techniques for Alzheimer's disease.

III. RESEARCH METHODOLOGY

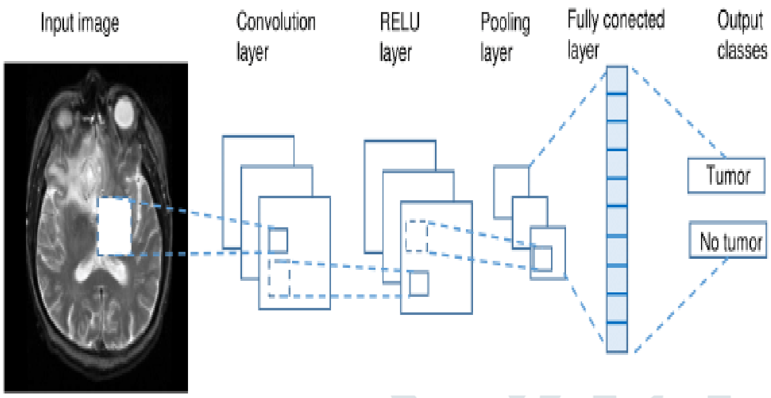

Fig: Research Methodology

In above figure, Pre-processing involves processes like conversion to grayscale image, noise removal and image reconstruction. Conversion to grey scale image is the most common pre-processing practice. After the image is converted to grayscale, then remove excess noise using different filtering methods. Segmentation of images is important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in a reasonable time.Feature extraction is an important step in the construction of any pattern classification and aims at the extraction of the relevant information that characterizes each class. Classification is the best approaches for identification of images like any kind of medical imaging. All classification algorithms are based on the prediction of image, where one or more features and that each of these features belongs to one of several classes. Classification is used to classify each item in a set of data into one of predefined set of classes or groups.

EXISTING SYSTEM

The fully connected layer has neurons that produce output of all neurons in a linear combination, which are taken from preceding layer and then is moved through nonlinearity. Finally for the last fully connected, a softmax layer is particularly used and then tuned finely for back-propagation to predict the class probability [3]. The result of each node varies from 0 to 1, and the total of nodes will always be 1. Finally the classification includes the deep network construction including the 3D CNN training and RNN model training. Then the results of fully connective layers are directly mapped using a softmax function [3]. The initial parameters that were trained by both 3dimensional CNN and the RNN network are established and then only the uppermost fully connective layer parameters and the softmax layer that was used for prediction are adjusted so that the dimensional and longitude features were united for distinct identification.

Disadvantages :

- LESS ACCURACY
- LOW EFFICIENCY

PROPOSED SYSTEM

proposed a model where longitudinal analysis is performed on consecutive MRI and is essential to design and compute the evolution of disease with time for the purpose of more precise diagnosis [3]. The actual process uses those features of morphological anomaly of the brain and the longitudinal difference in MRI and constructed classifier for distinguishing between the distinct groups. The MRI brain images of 6 time points that is for consecutive intervals in a gap of six months are taken as inputs from ADNI database. Then feature learning is done with the 3D Convolutional Neural Network. The CNN is followed by a pooling layer and have many ways for pooling, like collecting mean value otherwise the maximal, or definite sequence of neuron in the sectionIn today's society, medical care problems have become a hot topic, and problems such as the unbalance and insufficient allocation of medical resources has become increasingly apparent. In this situation, the application of ML has become the unavoidable trend in the current development of medical care. As early as 1972, the scientists in the University of Leeds in the UK has been trying to use artificial intelligence (ANN) algorithms to judge abdominal pain. Now, more and more researchers are committed to the combination of ML and medical care. The methods of pathological diagnosis of tumors, lung cancer, etc. by ML has gradually entered the field of vision. Some companies, such as Alibaba, Amazon, and Baidu have established their own research team working for it. At the same time, the demand of people also provides a new impetus for the research and development of ML, with promoting its continuous improvement.

Advantages

- Identifying Diseases and Diagnosis. ...
- Drug Discovery and Manufacturing. ...
- Medical Imaging Diagnosis. ...
- Personalized Medicine. ...
- Machine Learning-based Behavioural Modification. ...
- Smart Health Records. ...
- Clinical Trial and Research.

IV. RESULTS AND DISCUSSION

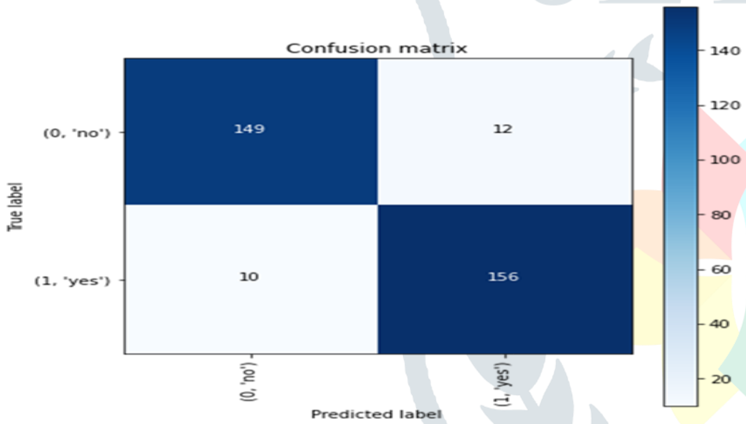

Figure2:Confusion matrix obtained for the dataset in neurology.

Metric	Value
Sensitivity	0.9397
Specificity	0.9254
Precisionscore	0.9328
Recallscore	0.9327
F1Score	0.9327

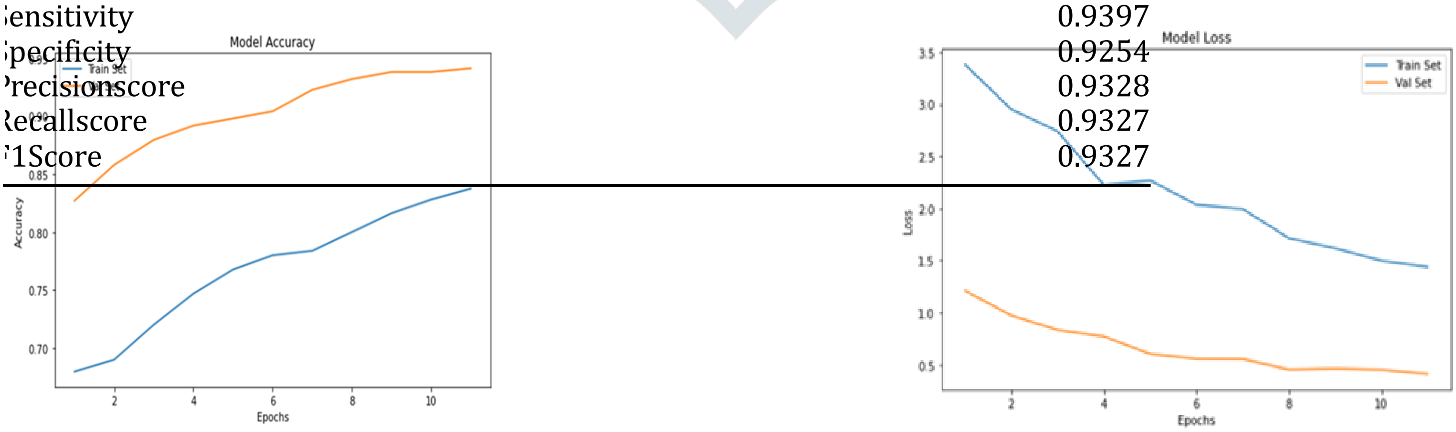

Figure3:Relationship between nmode lperformance (**a**)accuracyversusnumberofepochs ;(**b**)modellossversusnumberofepochs.

CONCLUSION

This paper reports relatively satisfactory performance on various tasks. Cho et al. partially answered the question of how many images are needed for training in medical image analysis. They found that a convolutional neural network (CNN) with a GoogLeNet architecture could classify individual axial CT images into one of six body regions (brain, neck, shoulder, chest, abdomen, pelvis) with 88-98% accuracy on a test set of 6,000 images, using just 200 training images. While classifying images into body regions is not a realistic medical analysis task, this suggests the problem of data scarcity may be surmountable. The high accuracy with a small dataset is likely due to the inherent homogeneity of medical images across patients, compared to the vast diversity of natural images (e.g. dogs in different breeds, colors, poses). Generative models like variational autoencoders (VAEs) and generative adversarial networks (GANs) may also help address data scarcity by creating synthetic medical 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.