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Brain Tumor Detection using Convolution Neural Network

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Abstract: *Brain tumors are a deadly disease with a life expectancy of only a few months in the most advanced stages. As a result, therapy planning is an important step in improving patients' quality of life. Various image techniques, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Ultrasound images, are commonly used to assess tumors in the brain, lung, liver, breast, prostate, and other organs. MRI images are used to diagnose brain tumors in particular in this work .However the massive amount of data generated by MRI scan thwarts manual classification of tumor vs non-tumor in a particular time. As a result, a reliable and automatic classification technique is required to reduce the human fatality rate. Deep Learning has sparked a lot of interest in recent years. It has been widely used in a variety of applications and has proven to be an effective machine learning technique for a variety of complicated issues. The use of Convolution Neural Networks (CNN) classification for automatic brain tumor detection is proposed in this paper. Small kernels are used to create the deeper architecture. When compared to all other state-of-the-art methodologies, experimental results demonstrate that CNN archives have a rate of 97.5 percent accuracy with little complexity.*

Keywords: Convolution Neural Networks (CNN), Kernels, Machine learning, Magnetic Resonance Imaging (MRI).

I. INTRODUCTION

Machine learning algorithms have the potential to be profoundly engaged in all sectors of medicine, from drug development to clinical decision making, dramatically transforming how medicine is done. The current success of machine learning algorithms for computer vision tasks comes at a good moment, as medical records are being increasingly digitalized. Between 2007 and 2012, the use of electronic health records (EHR) doubled. Medical images are an important aspect of a patient's electronic health record (EHR) and are currently examined by human radiologists, who are constrained by their speed, weariness, and experience. It takes years and a lot of money to train a trained radiologist, hence some health-care organizations use tel-radiology to outsource radiology reporting to lower-cost countries like India. The patient suffers from a delayed or incorrect diagnosis. As a result, using an automated, accurate, and efficient machine learning system to do medical image analysis is excellent. Medical image analysis is a hotbed of machine learning research, partially because the data is well-structured and labeled, and it's possible that this will be the first area where patients interact with working artificial intelligence systems. For two reasons, this is significant. To begin with, medical image analysis is a litmus test for whether artificial intelligence systems would genuinely improve patient outcomes and survival in terms of actual patient metrics. Second, it serves as a testbed for human-AI interaction, determining how amenable patients will be to non-human actors making or assisting them in making health-altering decisions.

II. RELATED WORKS

1. Trends in electronic health record system use among ofce-based physicians.
AUTHORS: Chun-Ju Hsiao, E. Hing, J. Ashman

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The National Ambulatory Medical Care Survey (NAMCS) is based on a national probability sample of non-federal 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. A survey on deep learning in medical image analysis.
AUTHORS: Geert Litjens ThijsKooi Babak, Ehteshamin Bejnordi Arnaud, Arindra Adioso Setio.
Deep Learning algorithm, in particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images. This paper reviews the major deep learning concepts pertinent to medical image analysis and summarizes over 300 contributions to the field, most of which appeared in the last year. We survey the use of deep learning for image classification, object detection, segmentation, registration, and other tasks. Concise overviews are provided of studies per application area: neuro, retinal, pulmonary, digital pathology, breast, cardiac, abdominal, musculoskeletal. We end with a summary of the current state-of-the-art, a critical discussion of open challenges and directions for future research.

3. A logical calculus of the ideas immanent in nervous activity.
AUTHORS: Warren S. McCulloch &Walter Pitts.
Because of the “all-or-none” character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behaviour of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neuro physiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

4. The perceptron: A probabilistic model for information storage and organization in the brain
AUTHORS: By Rosenblatt.
To answer the questions of how information about the physical world is sensed, in what form is information remembered, and how does information retained in memory influence recognition and behavior, a theory is developed for a hypothetical nervous system called a perceptron. The theory serves as a bridge between biophysics and psychology. It is possible to predict learning curves from neurological variables and vice versa. The quantitative statistical approach is fruitful in the understanding of the organization of cognitive systems. 18 references. (PsycINFO Database Record (c) 2016 APA, all rights reserved).

5. Receptive elds, binocular interaction and functional architecture in the cat's visual cortex
AUTHORS: D. H. Hubel and T. N. Wiesel.
What chiefly distinguishes cerebral cortex from other parts of the central nervous system is the great diversity of its cell types and inter-connexions. It would be astonishing if such a structure did not profoundly modify the response patterns of fibres coming into it. In the cat's visual cortex, the receptive field arrangements of single cells suggest that there is indeed a degree of complexity far exceeding anything yet seen at lower levels in the visual system. In a previous paper we described receptive fields of single cortical cells, observing responses to spots of light shone on one or both retinas (Hubel & Wiesel, 1959). In the present work this method is used to examine receptive fields of a more complex type (Part I) and to make additional observations on binocular interaction (Part II). This approach is necessary in order to understand the behaviour of individual cells, but it fails to deal with the problem of the relationship of one cell to its neighbours. In the past, the technique of recording evoked slow waves has been used with great success in studies of functional anatomy. It was employed by Talbot & Marshall (1941) and by Thompson, Woolsey & Talbot (1950) for

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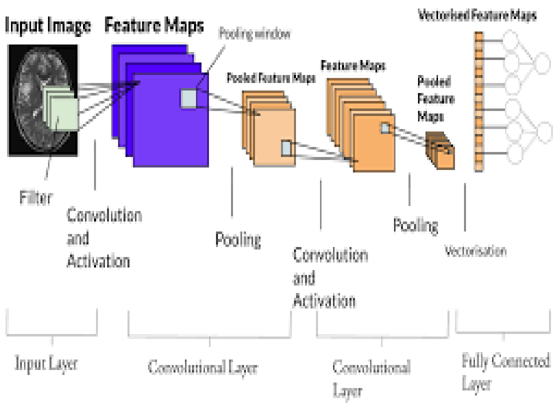
mapping out the visual cortex in the rabbit, cat, and monkey. Daniel & Whitteiidge (1959) have recently extended this work in the primate. Most of our present knowledge of retinotopic projections, binocular overlap, and the second visual area is based on these investigations. Yet the method of evoked potentials is valuable mainly for detecting behaviour common to large populations of neighbouring cells; it cannot differentiate functionally between areas of cortex smaller than about 1 mm2. To overcome this difficulty a method has in recent years been developed for studying cells separately or in small groups during long micro-electrode penetrations through nervous tissue. Responses are correlated with cell location by reconstructing the electrode tracks from histological material. These techniques have been applied to CAT VISUAL CORTEX 107 the somatic sensory cortex of the cat and monkey in a remarkable series of studies by Mountcastle (1957) and Powell & Mountcastle (1959). Their results show that the approach is a powerful one, capable of revealing systems of organization not hinted at by the known morphology. In Part III of the present paper we use this method in studying the functional architecture of the visual cortex.

6. Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition.
Authors: Kunihiko Fukushima.
A neural network model for a mechanism of visual pattern recognition is proposed in this paper. The network is self-organized by “learning without a teacher”, and acquires an ability to recognize stimulus patterns based on the geometrical similarity (Gestalt) of their shapes without affected by their positions. This network is given a nickname “neocognitron”. After completion of self-organization, the network has a structure similar to the hierarchy model of the visual nervous system proposed by Hubel and Wiesel. The network consists of an input layer (photoreceptor array) followed by a cascade connection of a number of modular structures, each of which is composed of two layers of cells connected in a cascade. The first layer of each module consists of “S-cells”, which show characteristics similar to simple cells or lower order hypercomplex cells, and the second layer consists of “C-cells” similar to complex cells or higher order hypercomplex cells. The afferent synapses to each S-cell have plasticity and are modifiable. The network has an ability of unsupervised learning: We do not need any “teacher” during the process of self-organization, and it is only needed to present a set of stimulus patterns repeatedly to the input layer of the network. The network has been simulated on a digital computer. After repetitive presentation of a set of stimulus patterns, each stimulus pattern has become to elicit an output only from one of the C-cell of the last layer, and conversely, this C-cell has become selectively responsive only to that stimulus pattern. That is, none of the C-cells of the last layer responds to more than one stimulus pattern. The response of the C-cells of the last layer is not affected by the pattern's position at all. Neither is it affected by a small change in shape nor in size of the stimulus pattern.

III. ARCHITECTURE



A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning system that can take an input image, assign relevance (learnable weights and biases) to various aspects/objects in the image, and distinguish between them. When compared to other classification techniques, the amount of pre-processing required by a ConvNet is significantly less. While basic approaches require hand-engineering of filters, ConvNets can learn these filters/characteristics with enough training.

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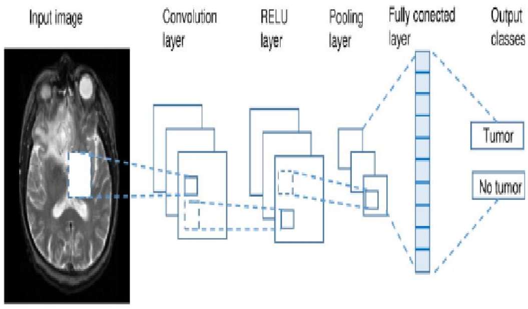
Through the application of suitable filters, a ConvNet may successfully capture the Spatial and Temporal dependencies in a picture. Due to the reduced number of parameters involved and the reusability of weights, the architecture performs superior fitting to the picture dataset. In other words, the network may be trained to better recognise the image's sophistication. The ConvNet's job is to compress the images into a format that is easier to process while preserving elements that are important for obtaining a decent prediction.

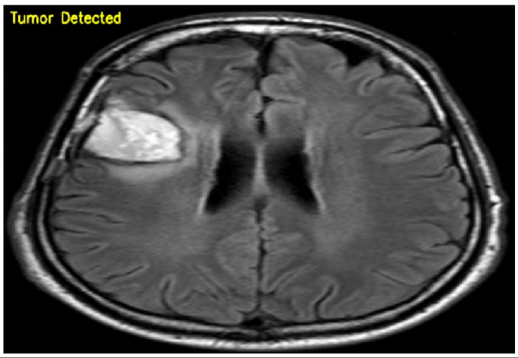


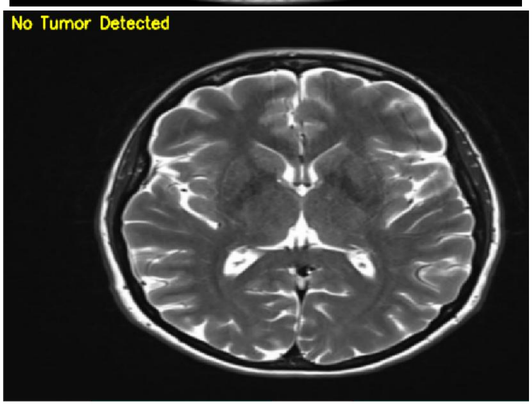
IV. EXPERIMENT AND RESULTS

We have used Convolution Neural Network to classify MRI images as tumor or non-tumor. The Data Set consists of Brain MRI images with tumors and with out tumors. These images and loaded using Open CV a python library and convert into a tensorflow record and feed to Convolutional Neural Network. The Layers used are Conv Layer (Relu Activation Function) , Max Pooling Layer, Conv Layer (Relu Activation Function) , Max Pooling Layer, then Flatten the output of Conv net and feed to Neural Network with two Dense Layers.

We could achieve 97% accuracy using this model.

4.1 Result





V. CONCLUSION

The absence of labelled datasets, which hampered training and performance, is a recurring topic in machine learning. On the other hand, it is widely known that having more data enhances performance. The dearth of data in medical

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image analysis is two-fold and more acute, generally there is lack of publicly available data, and high-quality labelled data is even scarce. Being able to accomplish classification with a small dataset is possibly due to the general intrinsic image homogeneity across different patients.

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