International Journal of Multidisciplinary Engineering in Current Research - IJMEC

Volume 10, Issue 5, May-2025, http://ijmec.com/, ISSN: 2456-4265

Deep Learning Applications In Medical Image Analysis-Brain Tumor

Darlanka Durga Sri Varsha
PG scholar, Department of MCA, CDNR collage, Bhimavaram, Andhra Pradesh.
V.Sarala
(Assistant Professor), Master of Computer Applications, DNR collage, Bhimavaram, Andhra Pradesh.

Abstract: 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 the machine learning algorithms as applied to medical image analysis, focusing on convolutional neural networks, and emphasizing clinical aspects of the _eld. The advantage of machine learning in an era of medical big data is that signi_cant 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 classi_cation, localization, detection, segmentation, and registration. We conclude by discussing research obstacles, emerging trends, and possible future directions

INTRODUCTION

Now more than ever technology has become an integral part of our life. With the evolution of the internet. Social media is trending these days. But as all the other things mis users will pop out sometimes late sometime early but there will be for sure. Now Cyber bullying is common these days.

Sites for social networking are excellent tools for communication within individuals. Use of social networking has become widespread over the years, though, in general people find immoral and unethical ways of negative stuff. We see this happening between teens or sometimes between young adults. One of the negative stuffs they do is bullying each other over the internet. In online environment we cannot easily said that whether someone is saying something just for fun or there may be other intention of him. Often, with just a joke, "or don't take it so seriously," they'll laugh it off Cyber bullying is the use of technology to harass, threaten, embarrass, or target another person. Often this internet fight results into real life threats for some individual. Some people have turned to suicide. It is necessary to stop such activities at the beginning. Any actions could be taken to avoid this for example if an individual's tweet/post is found offensive then maybe his/her account can be terminated or suspended for a particular period.

So, what is cyber bullying??

Cyber bullying is harassment, threatening, embarrassing or targeting someone for the purpose of having fun or even by well-planned means

II. BACKGROUND

Researches on Cyber bullying Incidents show that 11.4% of 720 young peoples surveyed in the NCT DELHI were victims of cyber bullying in a 2018 survey by Child Right and You, an NGO in India, and almost half of them did not even mention it to their teachers, parents or guardians. 22.8% aged 13-18 who used the internet for around 3 hours a day were vulnerable to Cyber bullying while 28% of people who use internet more than 4 hours a day were victims. There are so many other reports suggested us that the impact of Cyber bullying is affecting badly the peoples and children between age of 13 to 20 face so many difficulties in terms of health, mental fitness and their decision making capability in any work. Researchers suggest that every country should have to take this matter seriously and try to find solution. In 2016 an incident called Blue Whale Challenge led to lots of child suicides in Russia and other countries . It was a game that spread over different social networks and it was a relationship between an administrator and a

ISSN: 2456-4265
IJMEC 2025

participant. For fifty days certain tasks are given to participants . Initially they are easy like waking up at 4:30 AM or watching a horror movie . But later they escalated to self harm which let to suicides. The administrators were found later to be children between ages 12-14.

LITERATURE SURVEY:

1. Trends in electronic health record system use among ofce-based physicians: United states, 20072012

AUTHORS: Chun-Ju Hsiao, E. Hing, J. Ashman

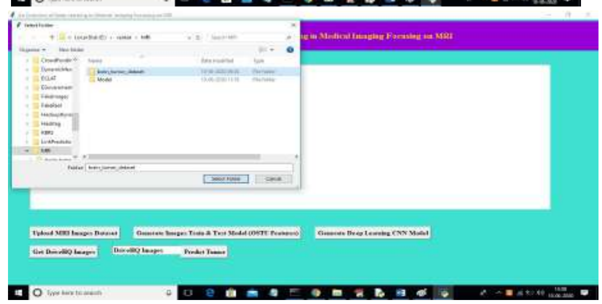
The National Ambulatory Medical Care Survey (NAMCS) is based on a national probability sample of nonfederal office-based physicians who see patients in an office setting. Prior to 2008, data on physician characteristics were collected through in-person interviews with physicians. To increase the sample 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.

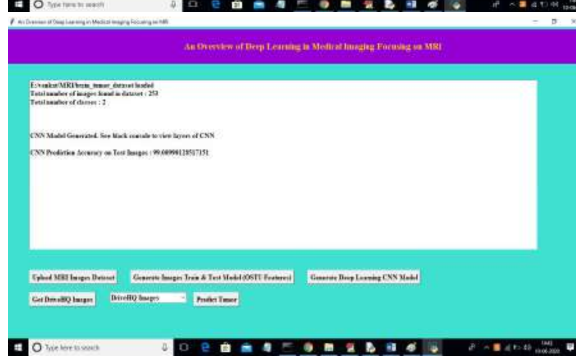
EXISTING SYSTEM

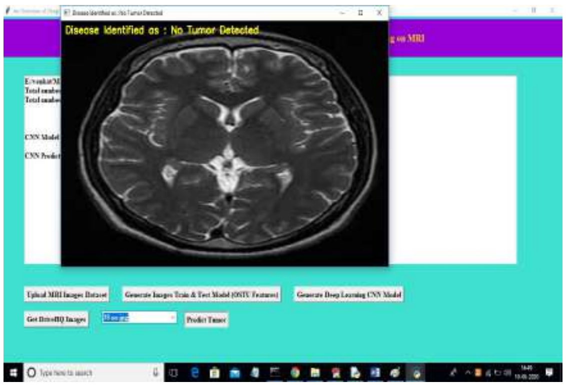
There is a myriad of imaging modalities, and the frequency of their use is increasing. Smith-Bindman *et al* looked at imaging use from 1996 to 2010 across six large integrated healthcare systems in the United States, involving 30.9 million imaging examinations. The authors found that over the study period, CT, MRI and PET usage increased 7.8%, 10% and 57% respectively.

PROPOSED SYSTEM

CNNs are the most researched machine learning algorithms in medical image analysis. The reason for this is that CNNs preserve spatial relationships when _ltering input images. As mentioned, spatial relationships are of crucial importance in radiology, for example, in how the edge of a bone joins with muscle, or where normal lung tissue interfaces with cancerous tissue.., a CNN takes an input image of raw pixels, and transforms it via Convolutional Layers, Rectied Linear Unit (RELU) Layers and Pooling Layers. This feeds into a nal Fully Connected Layer which assigns class scores or probabilities, thus classifying the input into the class with the highest probability.







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. While categorization into various body regions is not a realistic medical image analysis task, his report does suggest that the problem may be surmountable. Being able to accomplish classification with a small dataset is possibly due to the general intrinsic image homogeneity across different patients, as opposed to the near-infinite variety of natural images, such as a dog in various breeds, colors and poses.

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. 565–571.
[21] K. Kamnitsas et al., ''Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation,'' Med. Image Anal., vol. 36, pp. 61–78, Feb. 2017.
[22] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.