



人工智能(AI)与医学 赵屹 M.D. Ph.D. 中国科学院计算技术研究所 中科信息产业研究院精准医学中心









个人介绍



赵屹,中科院计算所生物信息P.I.博导;中科信息产业研究院精准医学研究所所长 北京大学医学部/清华大学

主要从事多组学生物信息分析研究、数据挖掘/机器学习/人工智能算法在医学应用 研究

近十年在*Cell stem cell, Cell metabolism, Nature structural and molecular biology,* Journal of Clinical Investigation, Journal of Hepatology, Genome Research, Trends in genetics, Nucleic Acids Research等国际著名期刊发表论文40余篇, 其中以第一作者及通信作者发表论文40篇,总SCI引用过2000次,单篇引最高345次,超过百次引用的文章7 篇。

European Research Council非编码RNA领域基金评审人;国际RNA联盟RNAcentral专家成员。 Frontier in Genetics编委;高校教材《分子诊断学》(中国医药科技出版社)第3版编委。 中国生物工程学会计算生物学与生物信息学专业委员,北京医学遗传学会委员,中华医学会心血管病学分会精准心血管病学学组委员,世中联计算医学委员会委员





人工智能概念



人工智能(Al. Artificial Intelligence)亦称机器智能,是指 有人工制造出来的系统所表现出来 的智能。

	1.	++	TN
-		隹基	 T
		$H \rightarrow h$	1-





















机器学习 参数N:N<10²







大数据和计算能力提升引爆这一次AI浪潮

DATA GROWTH







CPU MULTIPLE CORES

GPU

THOUSANDS OF CORES

50X BOOST IN DEEP LEARNING IN 3 YEARS



AlexNet training throughput based on 20 iterations, CPU: 1x E5-2680v3 12 Core 2.5GHz. 128GB System Memory, Ubuntu 14.04





ImageNet Challenge

IM GENET

- 1,000 object classes (categories).
- Images:
 - 1.2 M train
 - 100k test. 0



man's-finger

currant





人类对自然图片的 分类准确率大约为 95%

卷积神经网络的分 类准确2015年大约 为96%

深度学习在自然图 片识别方面达到了 人类水平





R-CNN: Regions with CNN features





Recurrent Neural Network





Convolutional Neural Network



"man in black shirt is playing guitar."



"a young boy is holding a baseball bat."



"construction worker in orange safety vest is working on road."



"a cat is sitting on a couch with a remote control."



"two young girls are playing with lego toy."



"boy is doing backflip on wakeboard."





"a woman holding a teddy bear in front of a mirror."

"a horse is standing in the middle of a road."

13





人工智能与医学影像



JAMA:检测视网膜眼底照片中糖尿病性视网膜病变的深度学习算法

使用深度卷积神经网络的专为图像分类而优 化过的神经网络模型,该网络使用 128175 张视网膜图像的数据集进行了训练,其中的 每一张图像都针对糖尿病性视网膜病变、糖 尿病性黄斑水肿和图像等级进行了 3 到 7 次评估。所得到的算法使用两个互相独立的 数据集进行了验证,其中的每张图像测试所 参考的标准是一个 7 或 8 人的美国认证眼 科医生中大多数人的意见。



A EyePACS-1: AUC, 99.1%; 95% CI, 98.8%-99.3%











Nature: 基于大脑核磁图像的自闭症风险预测

LETTER

Early brain development in infants at high risk for autism spectrum disorder

Heather Cody Hazlett^{1,2}, Hongbin Gu¹, Brent C. Munsell³, Sun Hyung Kim¹, Martin Styner¹, Jason J. Wolff⁴, Jed T. Elison⁵, Meghan R. Swanson², Hongtu Zhu⁶, Kelly N. Botteron⁷, D. Louis Collins¹¹, John N. Constantino⁷, Stephen R. Dager^{4,9}, Annette M. Estes^{9,10}, Alan C. Evans¹¹, Vladimir S. Fonov¹¹, Guido Gerig¹², Penelope Kostopoulos¹¹, Robert C. McKinstry¹³, Juhi Pandey¹⁴, Sarah Paterson¹⁵, John R. Pruett Jr⁷, Robert T. Schultz¹⁴, Dennis W. Shaw^{8,3}, Lonnie Zwaigenbaum¹⁶, Joseph Piven1,2 & the IBIS Network*

Brain enlargement has been observed in children with autism spectrum disorder (ASD), but the timing of this phenomenon, and the relationship between ASD and the appearance of behavioural symptoms, are unknown. Retrospective head circumference and at high familial risk of autism can provide insight into the early development of autism and have shown that characteristic social second year of life^{3,4}. These observations suggest that prospective brain-imaging studies of infants at high familial risk of ASD might identify early postnatal changes in brain volume that occur before an ASD diagnosis. In this prospective neuroimaging study of we show that hyperexpansion of the cortical surface area between 6 and 12 months of age precedes brain volume overgrowth observed diagnosed with autism at 24 months. Brain volume overgrowth information from magnetic resonance imaging of the brain of of ASD. 6-12-month-old individuals predicted the diagnosis of autism in individual high-risk children at 24 months (with a positive predictive value of 81% and a sensitivity of 88%). These findings not differ between groups from 6 to 12 months of age. However, pairdemonstrate that early brain changes occur during the period in which autistic behaviours are first emerging.

with ASD over twenty years ago5. Subsequent reports suggested that were later diagnosed with autism at 24 months of age or later⁹ (mean age, 32.5 months).

als from a longitudinal study comprising 318 infants at high familial risk for ASD (HR), of which 70 met clinical best-estimate criteria for ASD, who also did not meet the criteria for ASD at 24 months change rate (6-12 months) were observed in the HR-ASD group (Fig. 2).

(see Methods for diagnostic and exclusion criteria). The three groups were comparable in (mean) race/ethnicity (85% white), family inco maternal age at birth (33 years old), infant birth weight (8 lb), and gestational age at birth (39 weeks). The HR-ASD group had more males than longitudinal brain volume studies of two-year olds followed up the other two groups (83% of the HR-ASD group was male compared to at four years of age have provided evidence that increased brain volume may emerge early in development^{1,2}. Studies of infants in the LR group had a higher education level (Extended Data Table 1).

doi:10.1038/nature21369

Infants were evaluated at 6, 12 and 24 months of age, which included detailed behavioural assessments and high-resolution magnetic resodeficits in ASD emerge during the latter part of the first and in the nance imaging (MRI) of the brain, to prospectively investigate brain and behavioural trajectories during infancy. The analyses described below were conducted on a subset of 106 high-risk (n=15 HR-ASD; n=91 HR-neg) and 42 low-risk infants for whom all three MRI scans were successfully obtained. On the basis of our previous findings at 106 infants at high familial risk of ASD and 42 low-risk infants, 2-4 years of age2, we hypothesized that brain overgrowth in ASD begins before 24 months of age; that overgrowth is associated with hyperexpansion of the cortical surface area; and that these early brain changes between 12 and 24 months in 15 high-risk infants who were are temporally linked to the emergence of the defining behaviours of ASD. We also investigated whether differences in the development of was linked to the emergence and severity of autistic social deficits. brain characteristics might suggest early biomarkers (that is, occurring A deep-learning algorithm that primarily uses surface area before the onset of the defining behaviours of ASD) for the detection

We first examined group differences in the trajectories of brain growth rate (Fig. 1). The growth rate of the total brain volume (TBV) did wise comparisons at 24 months showed large effect sizes for HR-ASD compared to LR and HR-ASD compared to HR-neg. The HR-ASD We first reported increased brain volume in adolescents and adults group showed a significantly increased TBV growth rate in the second year compared to both the LR and HR-neg groups (Extended Data Table 2). that brain overgrowth in ASD may be most apparent during early In addition, the HR-ASD group showed a significantly increased surchildhood⁶⁻⁸. A study of infants at risk for ASD (33 high-risk and face area growth rate from 6 to 12 months of age compared to both 22 low-risk infants), scanned from 6 to 24 months of age, found the HR-neg and LR groups, with the most robust increases observed enlarged brain volume present at 12 and 24 months in the 10 infants in the left/right middle occipital gyrus, right cuneus and right lingual gyrus area (see Fig. 2). No group differences were observed in cortical hickness. We observed a significant correlation between surface area In the present study, we examined data from a subset of individu-growth rate of 6-12 months and enlargement in TBV at 24 months of age in all subjects ($r_{192} = 0.59$, P < 0.001), as well as in the combined HR subgroup (r130 = 0.63, P < 0.001). Raw means, standard deviations for ASD (HR-ASD) and 248 that did not meet the criteria for ASD and effect sizes for the group comparisons of TBV and surface area are (HR-neg) at 24 months of age, and 117 infants at low familial risk (LR) provided in Extended Data Table 3. Regional differences in surface area

¹Department of Psychiatry, University of North Carolina, Chapel Hill, North Carolina 27599, USA. ²Carolina Institute for Developmental Disabilities, Chapel Hill, North Carolina 27599, USA. ³College of Diarleston, Ovarleston, South Carolina 29424, USA. ⁴Department of Educational Psychology, University of Minnesota, Minnesota 55455, USA. ⁴Institute of Child Development, University of Minnesota, Minnesota 55455, USA 4Department of Biostatistics, University of North Carolina, Chapel Hill, North Carolina 27599, USA. 1Department of Psychiatry, Washington University School of Medicine, St. Louis, Missouri 63110, USA. *Department of Radiology, University of Washington, Seattle, Washington 98105, USA. *Center on Human Developme and Disability, University of Washington, Seattle, Washington 198105, USA. ¹⁰Department of Speech and Hearing Sciences, University of Washington, Seattle, Washington 98105, USA. ¹¹Montheat Neurological Institute, McGill University, Montheat, Quebec H3A 004, Canada. ¹²Tandon School of Engineering, New York University, New York, New York 1003, USA. ¹³Mallinciredt Institute of lags, Washington University, SL Louis, Missouri 63110, USA. 14Center for Autism Research, The Children's Hospital of Philadelphia and University of Pennsylvania, Philadelphia, Pennsy 19104, USA "Department of Psychology, Temple University, Philadelphia, Pernsylvania 19122, USA. "Department of Pediatrics, University of Alberta, Edmonton, Alberta T60 2R3, Canada. *A list of participants and their affiliations appears at the end of the paper.

348 | NATURE | VOL 542 | 16 FEBRUARY 2017

#2 2017 Macmillan Publishers Limited, part of Springer Nature, All rights reserved

Figure 3 | Visualization of cortical regions with surface area measurements among the top 40 features contributing to the reduction in deep learning dimensionality. The cortical regions with surface area measurements that were among the top 40 features obtained from the nonlinear deep learning approach are visualized. The top 10 deep learning features observed include: surface area at 6 months in the right and left

> superior frontal gyrus, post-central gyrus, and inferior parietal gyri, and intracranial volume at 6 months. These features produced by the deep learning approach are highly consistent with those observed using an alternative approach (linear sparse learning) (Extended Data Fig. 1). Two tables listing the top 40 features from the deep learning approach and sparse learning are provided in Supplementary Tables 2 and 3.

Figure 2. Proposed Two-stage prediction pipeline that includes a non-linear dimension reduction step followed by a SVM classification step



预测2岁前的自闭症高危儿童 (家族史)是否会在2岁之后 被诊断为自闭症。

人工智能判别法(Hazlett et al. 2017) 准确度88%

传统行为问卷调查法 (Charman 2014)准确度50%





一位资深病理学家花了整整30个小时,仔仔细细分析了130张切片,依 然以73.3%的准确率完败准确率达88.5%的人工智能。



乳腺癌影像学数据





乳腺钼靶

10,000例

有标注的

乳腺B超









- 分级诊疗要么让有限的 专家资源下沉,要么复 制更多的专家(AI)。
- 国家卫计委发布了2017
 版"人工智能辅助诊断
 技术管理规范"及"人
 工智能辅助诊断技术临
 床应用质量控制指标"

0











[0]

鉴定分类疾病 精确度量敏感区域 提供影像学报告

辅助诊疗

辅助医生诊断疾病 辅助医生确定治疗方案 分级诊疗提高基层诊断水平





基因	组学	
寻找	'兴趣'	位点
寻找	基因型	表型关系



健康管理

构建个人健康档案 关注个人身体健康变化 预测疾病风险、降低风险 辅助慢性病人日常生活







微信: ebiomed