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# Pathological Brain Detection



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## Preface

Machine learning is a prosperous research field in computer science. It has evolved from an initial expert system to a system demonstrating deep-learning techniques. In 2016 the best known breaking news in this field was that AlphaGo, developed by Google, beat the world champion, Lee Sedol, in a Go match in Seoul. This drove the burning enthusiasm of scholars to apply machine learning to other important fields. This book describes the application of machine learning to radiology.

Currently, radiologists and neuroradiologists face the challenge of detecting lesions both rapidly and accurately. Lesions of various diseases in their prodromal phase are not easy to detect with human eyes. However, computers can easily distinguish a slight change in brain's structure. The ability to distinguish a slight gray-level difference can be pivotal in making an accurate and reliable diagnosis.

This book summarizes the latest advances in pathological brain detection using machine-learning approaches. It presents state-of-the-art computer algorithms, which can help perform automatic medical diagnoses in the brain.

This book is for undergraduate and graduate students in the field of computer science. It may also be useful to engineers, scientists, neuroradiologists, and researchers who are interested in pathological brain detection.

This book is organized in the following manner. Chapter 1 provides the basics of pathological brain detection. In this chapter various brain diseases are categorized into four main types.

Chapter 2 introduces neuroimaging modality from a historical view. Pneumoencephalography, cerebral angiography, computerized tomography, positron emission tomography, and single photon emission computerized tomography are all described in this chapter. There is a specific emphasis given to magnetic resonance imaging.

Chapter 3 presents standard image preprocessing techniques, including image denoising, skull stripping, slice selection, spatial and intensity normalization, and image enhancement—subtleties essential to pathological brain detection procedures.

The next six chapters are the basic components of a standard computer-aided diagnosis system. Chapter 4 shows how to extract features from brain images. Chapter 5 describes multiscale and multiresolution features. Chapter 6 introduces wavelet families and variants. Chapter 7 expatiates dimensionality reduction techniques. Chapter 8 compares the latest classifiers. Chapter 9 covers the latest optimization techniques used to train classifiers. All six chapters form a canonical procedure of developing a smart diagnostic system. Each individual chapter is a description of the background reviews of corresponding methods, and introduces and compares related state-of-the-art methods.

Chapter 10 compares current state-of-the-art pathological brain detection systems. Their shortcomings are analyzed to suggest the possible direction of future research. Finally, Chap. 11 shows deep-learning technique results for cerebral microbleeds. The convolutional neural network is found to give better results than an autoencoder and traditional computer vision–based methods.

The four contributors of this book are Dr. Shui-Hua Wang, Prof. Yu-Dong Zhang, Prof. Zhengchao Dong, and Dr. Preetha Phillips. The four authors have a long history of cooperation over the past 10 years. The team has published over 100 peer-reviewed papers in famous international journals. We hope this book might benefit your study and work.

Jiaozuo/Nanjing, China Leicester, UK/Jiaozuo, China New York, USA Shepherdstown/St. Lewisburg, USA Shui-Hua Wang Yu-Dong Zhang Zhengchao Dong Preetha Phillips

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# Acronyms

ABC	Artificial bee colony
ACO	Ant colony optimization
AD	Alzheimer's disease
AE	Autoencoder
AF	Activation function
AFNI	Analysis of functional neuroImages
AI	Artificial intelligence
AIS	Artificial immune system
ASP	Algorithm-specific parameter
BBB	Blood-brain barrier
BBO	Biogeography-based optimization
BD	Bhattacharyya distance
BER	Bayes error rate
BET	Brain extraction tool
BF	Bilateral filter
BFGS	Broyden fletcher goldfarb shannon
BGS	Boltzmann–Gibbs–Shannon
BOLD	Blood oxygen level dependent
BP	Backpropagation
CAD	Computer-aided diagnosis
CART	Classification and regression tree
CBF	Cerebral blood flow
CCP	Common controlling parameter
CDF	Cumulative distribution function
CJD	Creutzfeldt-Jakob disease
CLAHE	Contrast-limited adaptive histogram equalization
CMB	Cerebral microbleed
CNN	Convolutional neural network
CSA	Clonal selection algorithm
CSF	Cerebrospinal fluid

CSI	Chemical shift imaging
СТ	Computerized tomography
CWT	Continuous wavelet transform
DAE	Denoising autoencoder
DAG	Directed acyclic graph
db	Daubechies (wavelet family)
DCA	Dendritic cell algorithm
DCT	Discrete cosine transform
DE	Differential evolution
DFRFT	Discrete fractional Fourier transform
DFT	Discrete Fourier transform
DNN	Deep neural network
DR	Dimensionality reduction
DST	Discrete sine transform
DT	Decision tree
DTCWT	Dual-tree complex wavelet transform
DTI	Diffusion tensor imaging
DWT	Discrete wavelet transform
EEG	Electroencephalogram
EELM	Evolutionary extreme learning machine
ELM	Extreme learning machine
EM	Expectation-maximization
EP	Evolutionary programming
ERM	Empirical risk minimization
ES	Evolution strategy
FA	Firefly algorithm
FDG	Fludeoxyglucose
FE	Frequency encoding
FFT	Fast Fourier transform
FLIRT	FMRIB's linear image registration tool
FMF	Fuzzy membership function
fMRI	Functional magnetic resonance imaging
FMRIB	Oxford Centre for Functional MRI of the Brain
FNIRT	FMRIB's nonlinear image registration tool
FNN	Feed-forward neural network
FRFT	Fractional Fourier transform
FSL	FMRIB's software library
FSVM	Fuzzy support vector machine
FT	Fourier transform
GA	Genetic algorithm
GEPSVM	Generalized eigenvalue proximal support vector machine
GLCM	Gray-level co-occurrence matrix
GM	Gray matter
GP	Genetic programming
GS	Grid search

GSO	Glowworm swarm optimization
GTB	Gradient tree boosting
HC	Healthy control
HE	Histogram equalization
HIV	Human immunodeficiency virus
HMI	Hu moment invariant
HPF	High-pass filter
HSI	Habitat suitability index
ICV	Inter-class variance
IDFT	Inverse discrete Fourier transform
IELM	Incremental extreme learning machine
IG	Information gain
INA	Immune network algorithm
kFCV	k-fold cross validation
kNN	k-nearest neighbor
KPCA	Kernel principal component analysis
LCDG	Linear combination of discrete Gaussians
LOOCV	Leave-one-out cross validation
LOSI	Logistic sigmoid
LPF	Low-pass filter
LPOCV	Leave- <i>p</i> -out cross validation
LRC	Linear regression classifier
LReLU	Leaky rectified linear unit
LSE	Least-squares estimation
MARS	Microbleed anatomical rating scale
MCCV	Monte Carlo cross validation
MD	Mahalanobis distance
MGRF	Markov–Gibbs random field
MIP	Maximum intensity project
MLP	Multilayer perceptron
MNI	Montreal Neurological Institute
MR	Magnetic resonance
MRA	Magnetic resonance angiography
MRI	Magnetic resonance imaging
MRSI	Magnetic resonance spectroscopic imaging
MRST	Multiple radial symmetry transform
MSE	Mean squared error
MWV	Max-wins-voting
NBC	Naive Bayes classifier
NLM	Non-local means
NPSVM	Non-parallel support vector machine
NSA	Negative selection algorithm
ONN	One-nearest neighbor
OPELM	Optimally pruned extreme learning machine
OSELM	Online sequential extreme learning machine

PBD	Pathological brain detection
PC	Principal component
PCA	Principal component analysis
PDF	Probability density function
PE	Phase encoding
PEG	Pneumoencephalography
PET	Positron emission tomography
PKPCA	Polynomial kernel principal component analysis
PNN	Probabilistic neural network
PPCA	Probabilistic principal component analysis
PR	Pattern recognition
PSO	Particle swarm optimization
PZM	Pseudo Zernike moment
PZP	Pseudo Zernike polynomial
QMF	Quadrature mirror filter
QP	Quadratic programming
RAP	Rank-based average pooling
RBF	Radial basis function
RBFNN	Radial basis function neural network
ReLU	Rectified linear unit
RF	Radio frequency (Chap. 2)
RF	Random forest (Chaps. 8 and 11)
RKPCA	Radial basis function kernel principal component analysis
RN	Repetition number
ROI	Region of interest
RQ	Rayleigh quotient
RSA	Restarted simulated annealing
RST	Rough set theory
SA	Simulated annealing
SAE	Sparse autoencoder
SAH	Subarachnoid hemorrhage
SCGD	Scaled conjugate gradient descent
SCV	Stratified cross validation
SDE	Semidefinite embedding
SI	Swarm intelligence
SIV	Suitability index variable
SL	Supervised learning
SNP	Sliding neighborhood processing
SNR	Signal-to-noise ratio
SPAIR	Spectrally adiabatic inversion recovery
SPECT	Single-photon emission computed tomography
SPM	Statistical parametric mapping
SSL	Semi-supervised learning
STFT	Short-time Fourier transform
STIR	short $T_1$ inversion recovery

STT	Student's t-test
SVM	Support vector machine
SVS	Single-voxel spectroscopy
SWI	Susceptibility weighted imaging
SWT	Stationary wavelet transform
TE	Echo time
TIA	Transient ischemic attack
TL	Tabu list
TLE	Temporal lobe epilepsy
TR	Repetition time
TS	Tabu search
TSVM	Twin support vector machine
UTFD	Unified time-frequency domain
UWT	Undecimated wavelet transform
WM	White matter
WNN	Weighted nearest neighbor
WPT	Wavelet packet transform
WT	Wavelet transform
WTA	Winner-take-all
WTT	Welch's t-test
ZM	Zernike moment
ZP	Zernike polynomial

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