ML in healthcare

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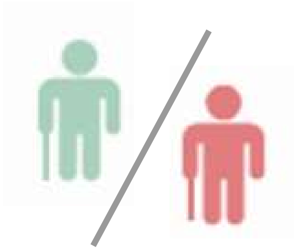
Machine learning applied to medical imaging



Diagnosis (early/differential)

is the patient healthy?

Prognosis

what will be the course of the disease?

Screening

are the patients -within a population- healthy?

Treatment addressing

will this therapy be effective for this patient?

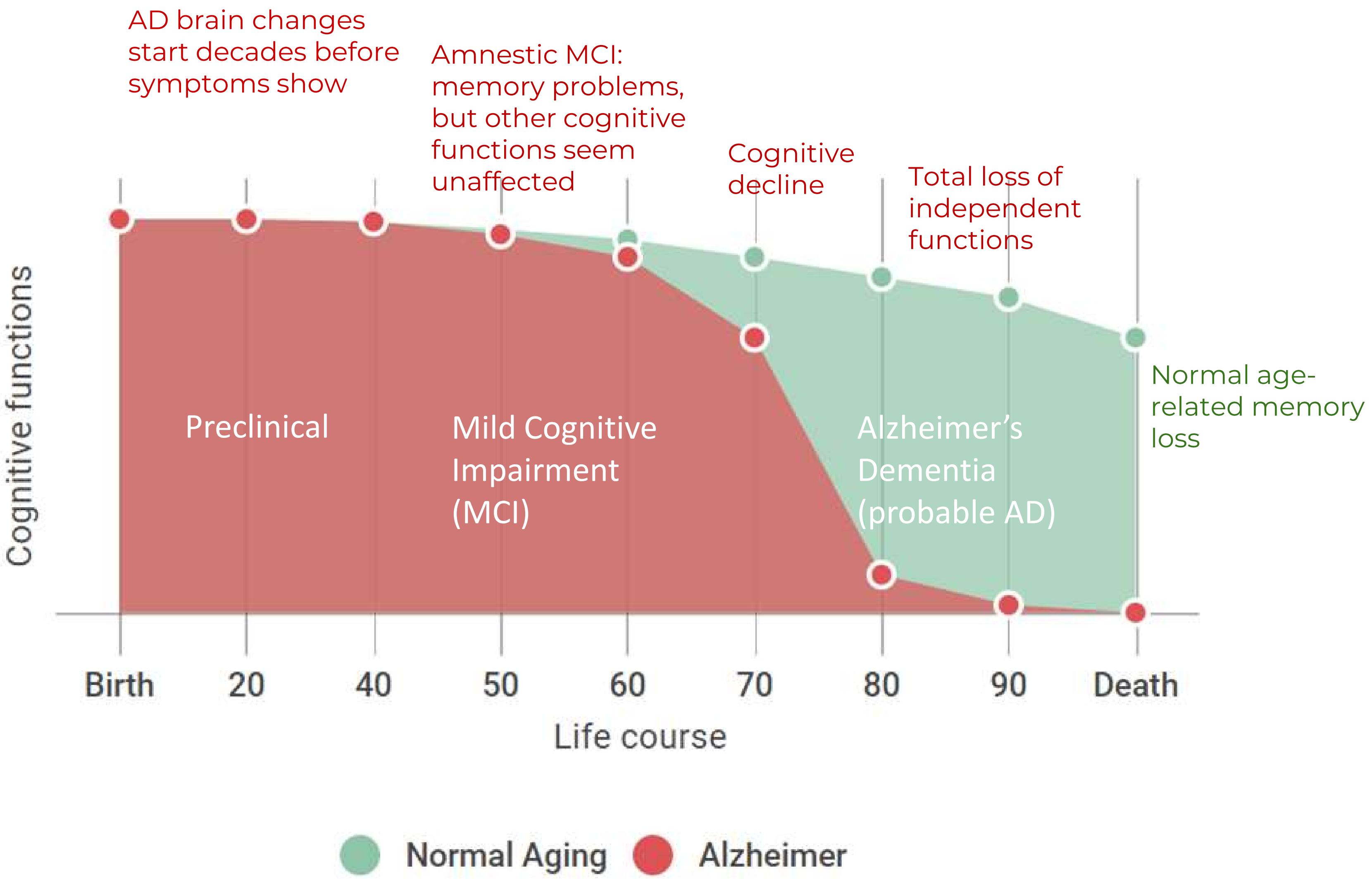
ML Models | Examples

(using different types of data)

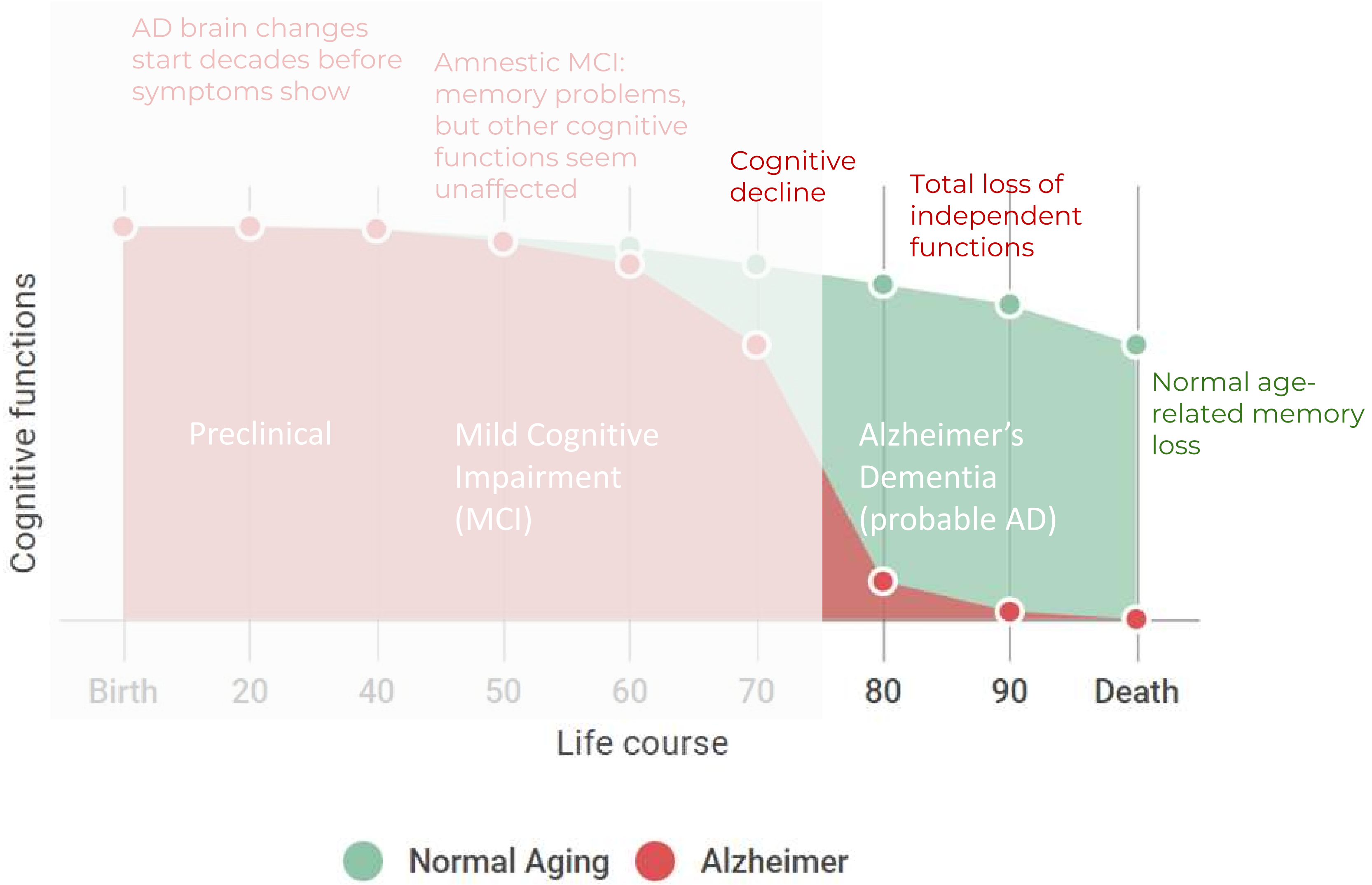
ML models | Examples

Alzheimer's Disease

ML models | Examples



ML models | Examples



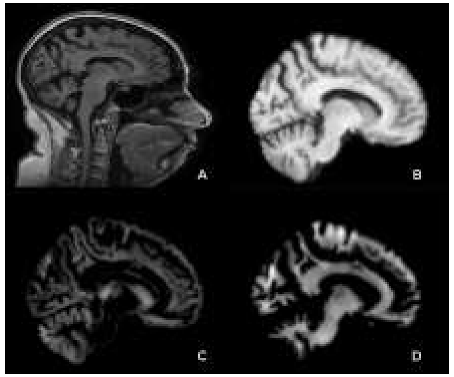
ML models | Examples

Clinical Diagnosis of Alzheimer's Disease

162	134	76	137
CN	MCInc	MCIc	AD

A dataset
of 509 subjects

Structural MRI
T1 weighted
1.5 Tesla

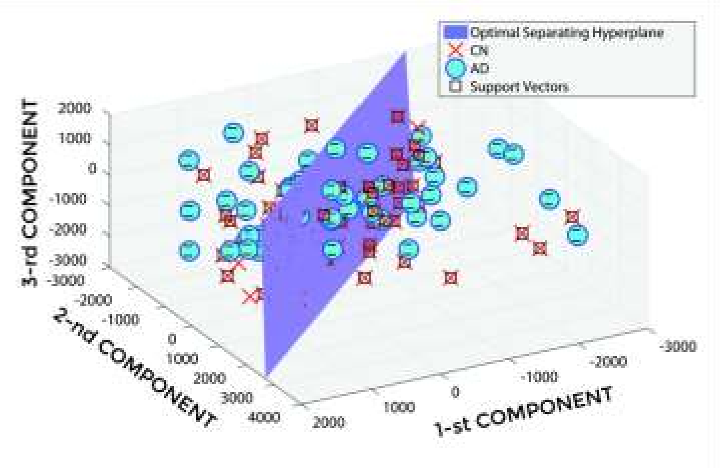


AD **Alzheimer's Disease**
MCIc Mild Cognitive Impairment, converting to Alzheimer's Dementia
MCInc Mild Cognitive Impairment, not converting to Alzheimer's Dementia
CN Cognitively-Normal subjects

Magnetic resonance imaging biomarkers for the early diagnosis of Alzheimer's disease: A machine learning approach.
Salvatore et al. 2015, Frontiers in Neuroscience.

ML models | Examples

Clinical Diagnosis			Accuracy (automatic classification)
AD	vs	CN	76%
MCIc	vs	CN	72%
MCIc	vs	MCInc	66%



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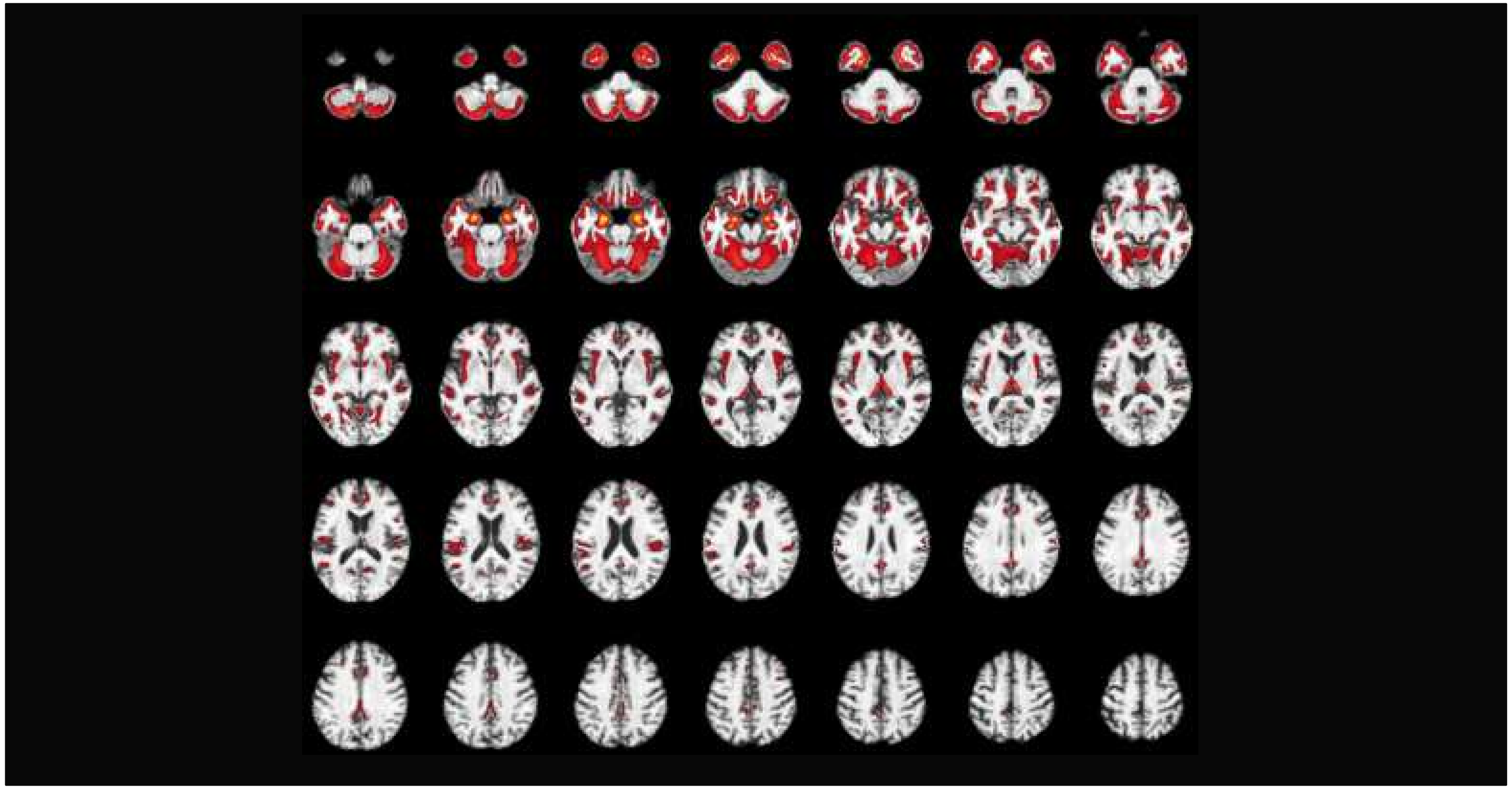
ML models | Examples



Best Structural-MRI Predictors

AD vs CN

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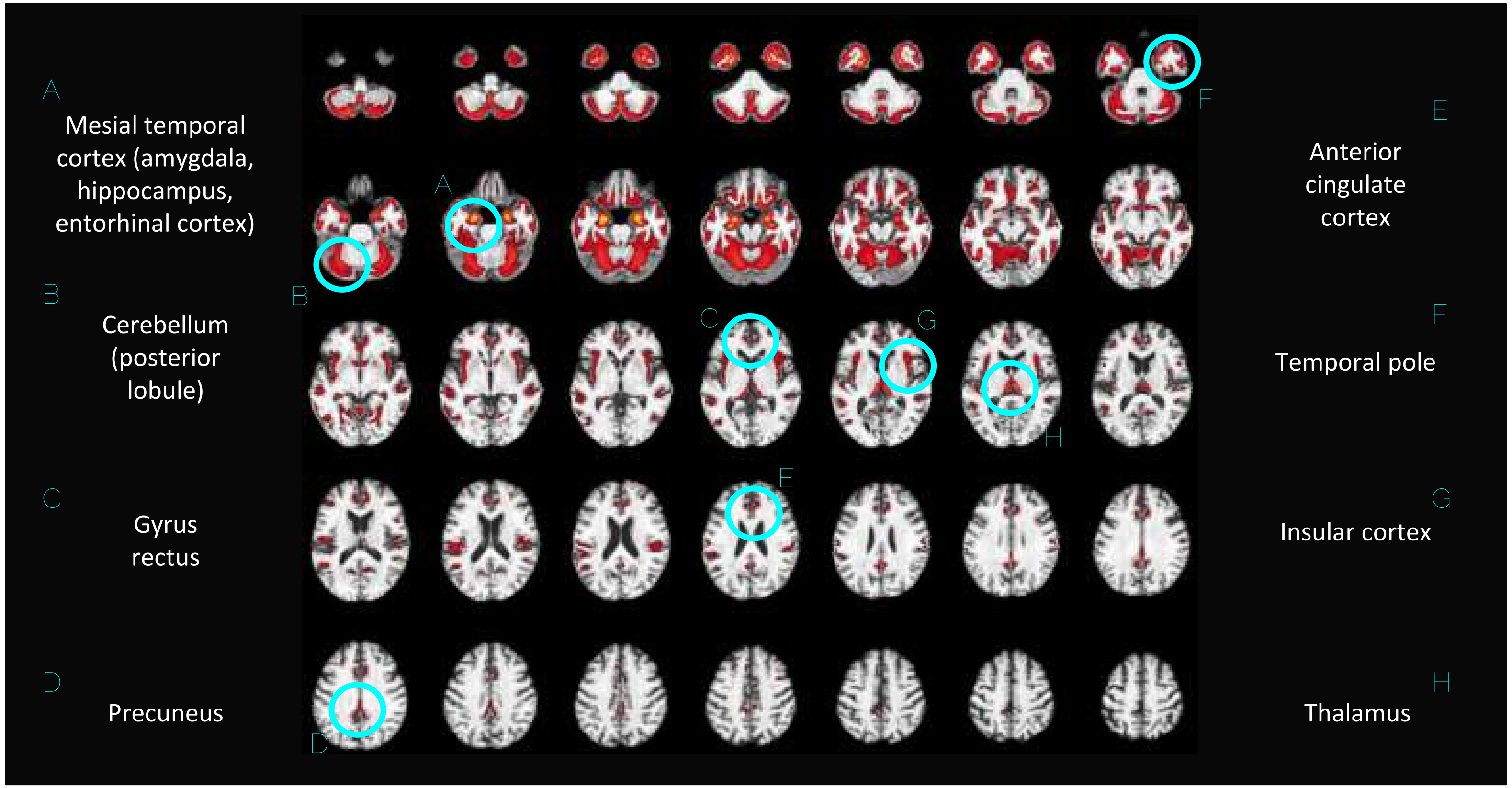
ML models | Examples



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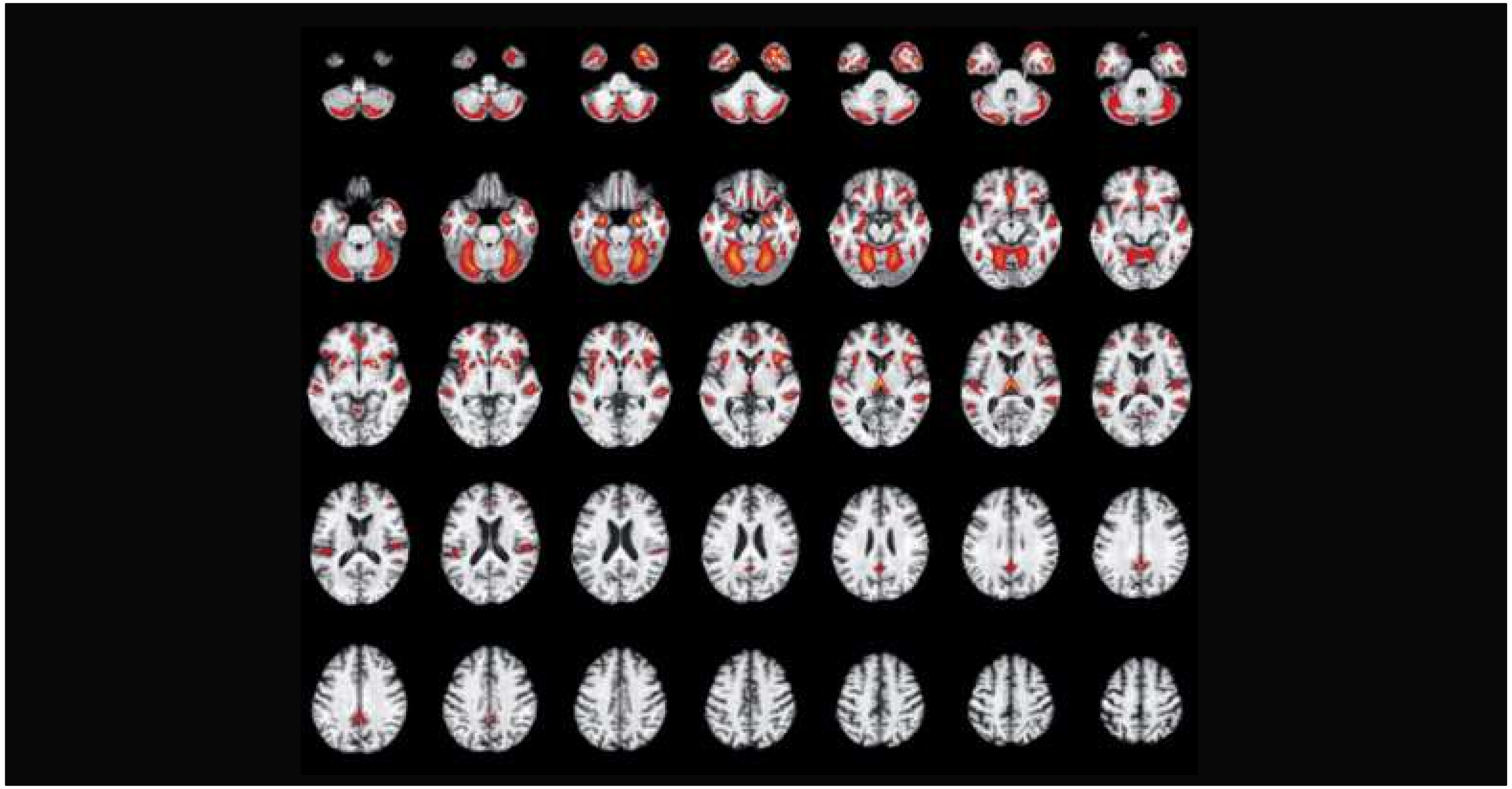
ML models | Examples



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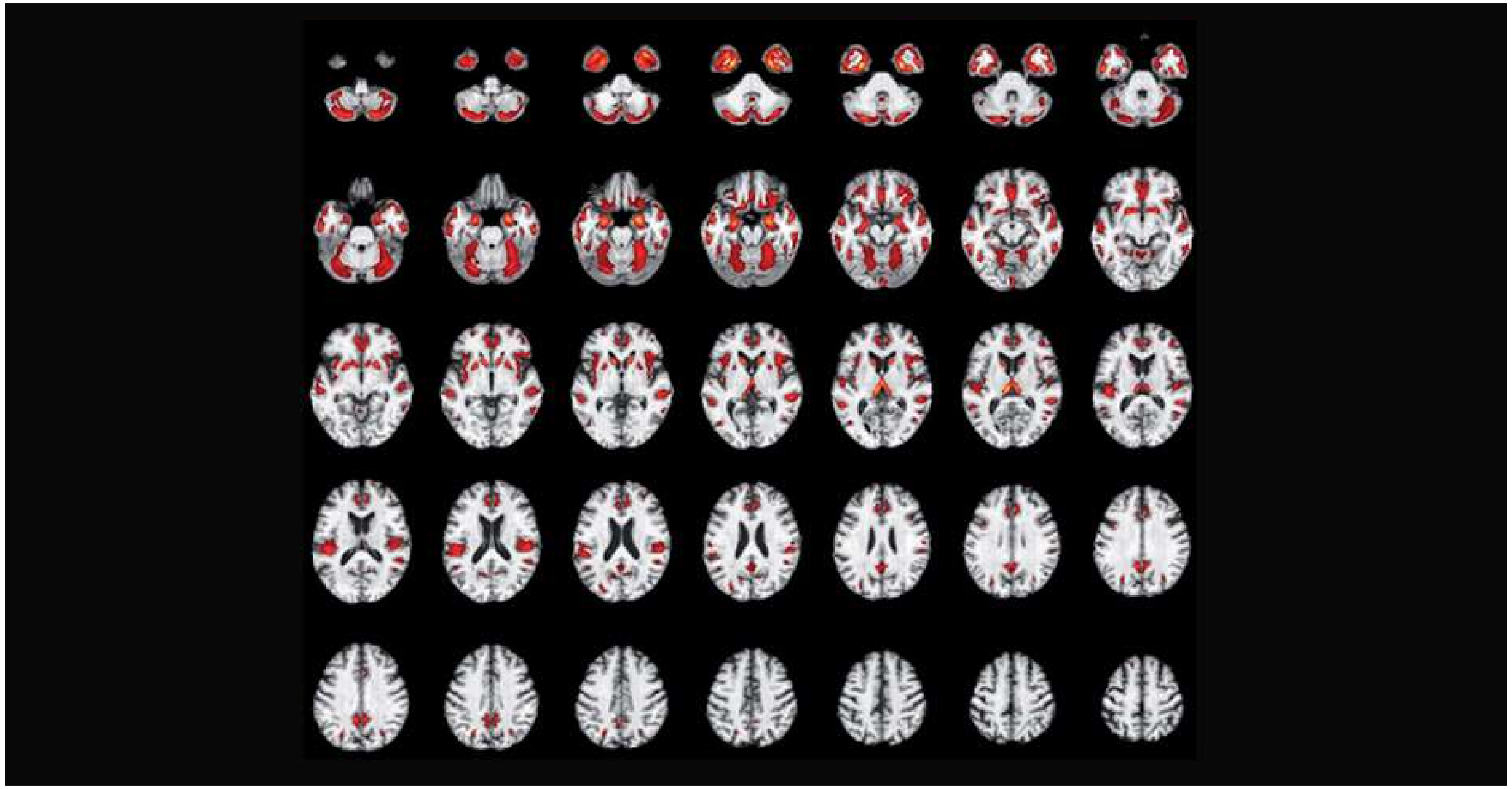
ML models | Examples



Best Structural-MRI Predictors

MCIc vs MCInc

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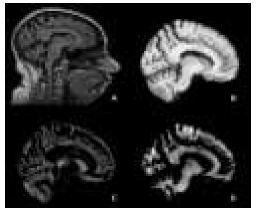
ML models | Examples

Clinical Diagnosis of AD at 24 months follow up

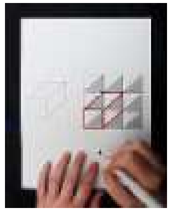
CN	MCInc	MCIc	AD
50	50	50	50

A dataset
of 200 subjects

Structural MRI
T1 weighted
1.5 Tesla



65 scores/subscores
from 7 neuro-
psychological tests



Timeline
months

0	6	12	24
Measure #1	Measure #2	Measure #3	Diagnosis

MRI characterizes the progressive course of AD and predicts conversion to Alzheimer's dementia twenty-four months before probable diagnosis. *Salvatore et al. 2018, Frontiers in Aging Neuroscience.*

ML models | Examples

Clinical Diagnosis (24 months follow up)

AD + MCIc

vs

MCInc + CN

Accuracy (sen/spe)

MRI	MRI + NPS
79% (79/78)	85% (83/87)

24 months before stable diagnosis

MRI characterizes the progressive course of AD and predicts conversion to Alzheimer's dementia twenty-four months before probable diagnosis. *Salvatore et al. 2018, Frontiers in Aging Neuroscience.*

ML models | Examples

Best Neuropsychological Predictors

24 months before stable diagnosis

Ability in remembering appointments, family occasions, holidays, medications in FAQ
Functional abilities

Ability in writing checks, paying bills, or balancing checkbook in FAQ
Functional abilities

Ability in assembling tax records, business affairs in FAQ
Functional abilities

Total score of trial 5 in AVLT
Memory and learning

Ability in keeping track of current events in FAQ
Functional abilities

Total intrusions of trial 1 in AVLT
Memory and learning

Correct answers in the Backwards task in Digit-Span Test
Working memory

Correct answers in Vegetables task in Category Fluency Test
Language

Correct answers after a 30-min delay in AVLT
Memory and learning

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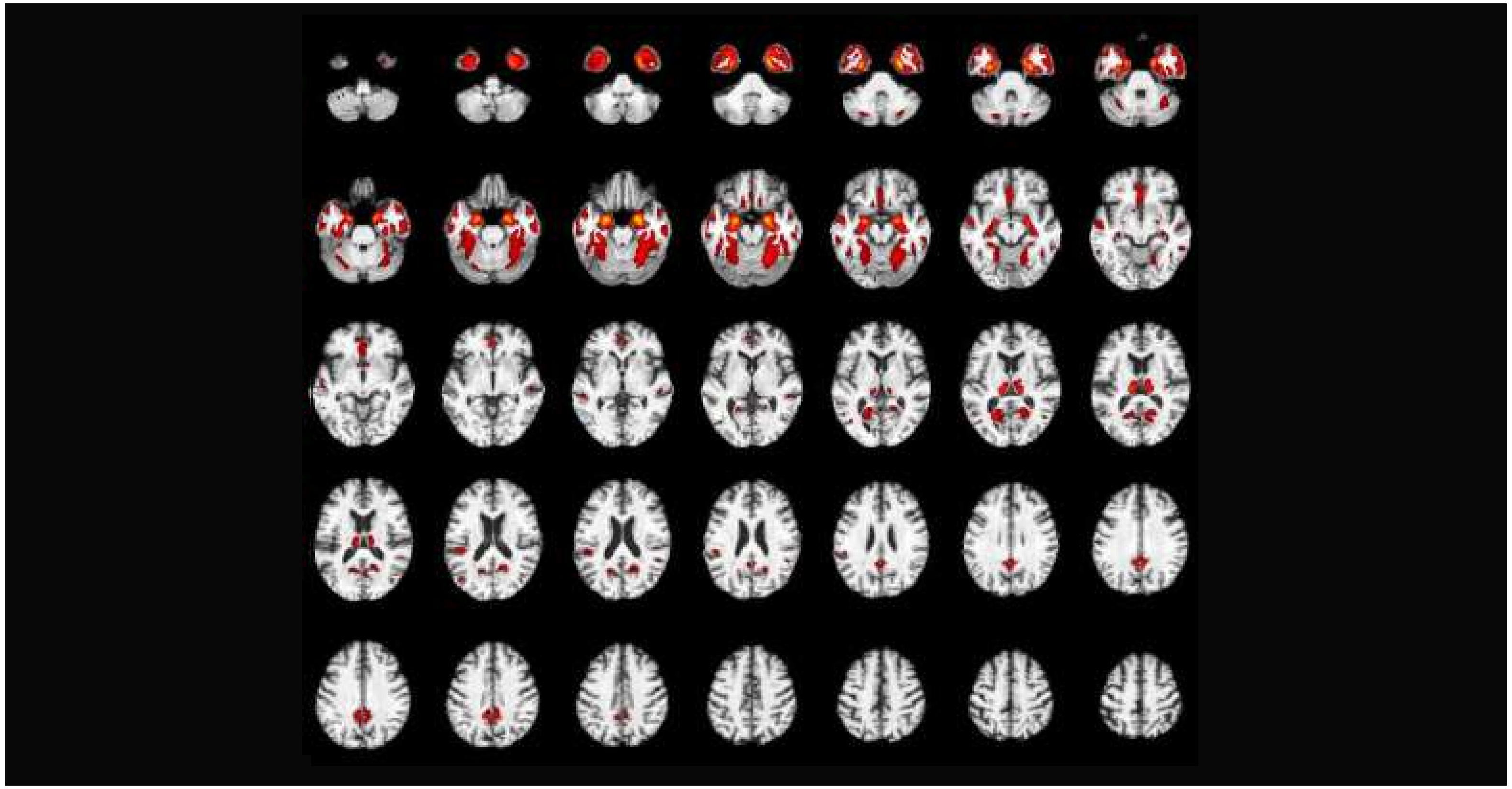
ML models | Examples



Best Structural-MRI Predictors

24 months before stable diagnosis

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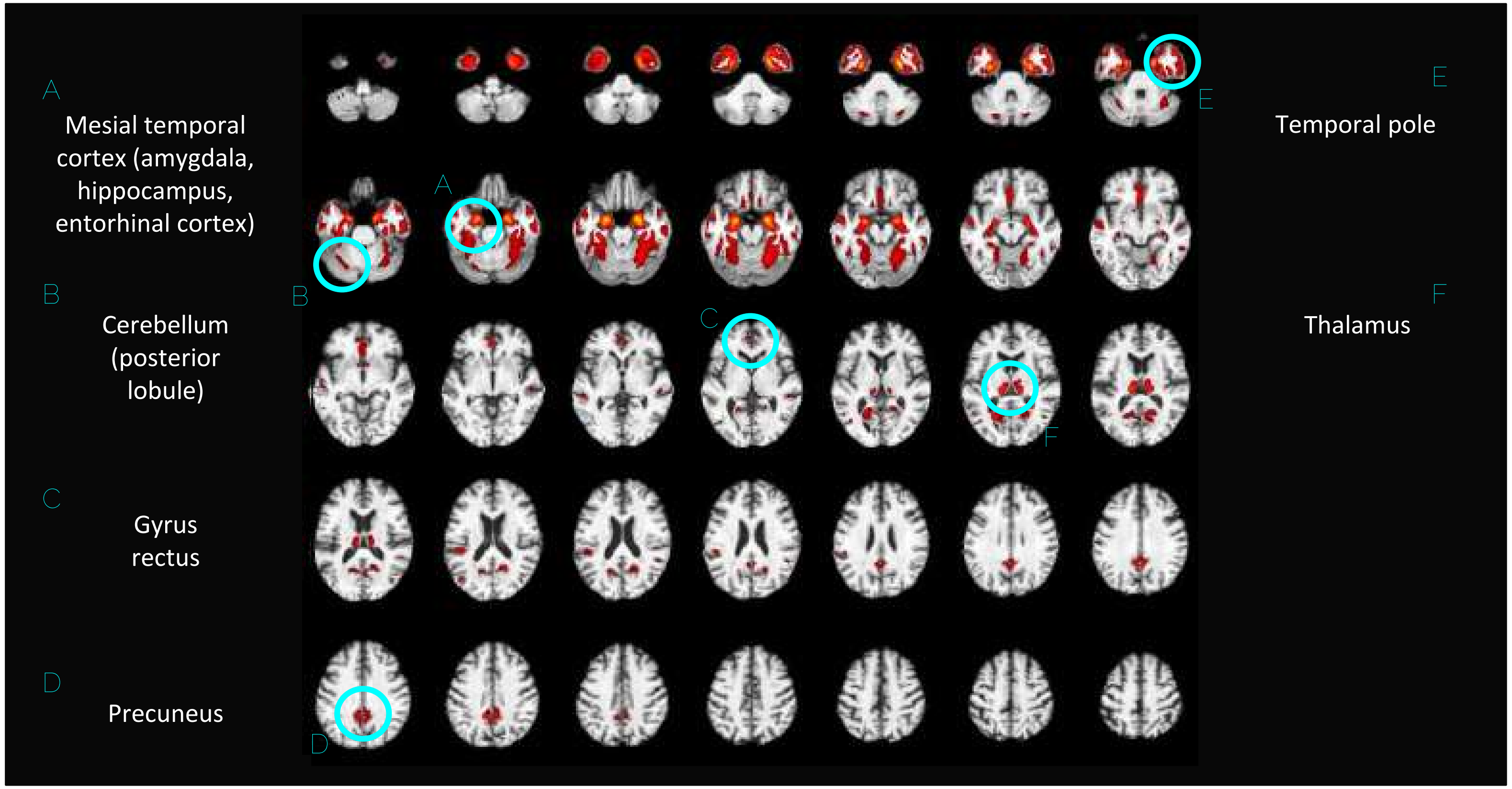
ML models | Examples



Best Structural-MRI Predictors

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ML models | Examples

Autism Spectrum Disorder

ML models | Examples

Confirm a motor signature of autism

15

TD

15

ASD

A dataset of 30
pre-school children (~3 years old)

17 kinematic features
collected during a reach-to-drop task

ASD **Autism Spectrum Disorder**
TD Typically-developing children

Use of machine learning to identify children with autism and their motor abnormalities. *Crippa, Salvatore et al. 2015, Journal of Autism and Developmental Disorders.*

ML models | Examples

Fig. 1 The experimental task consisted of grasping a rubber ball (**2**) that was placed over a support (see **1**, a); that is, a reach-to-grasp movement before they dropped it in a hole (**3**). The hole (**1**, c) was located inside a see-through *square box* (21 cm high, 20 cm wide) and was large enough not to require fine movements. The goal area is transparent to allow seeing through. 4 markers are placed on the basket under the goal area, 2 on the ball and 3 on each hand (attached to the ulnar and radial surfaces of the participant's wrist and to the hand dorsum on the 4th and 5th metacarpals)

sub-movement 1
the movement necessary to reach the ball and place it on its support

- # movement units
- total movement duration
- peak velocity
- peak acceleration
- time of peak acceleration
- peak deceleration
- time of peak deceleration

sub-movement 2
the movement to transport the ball from a support to the target hole

- # movement units
- total movement duration
- peak velocity
- peak acceleration
- time of peak acceleration
- peak deceleration
- time of peak deceleration
- wrist angle

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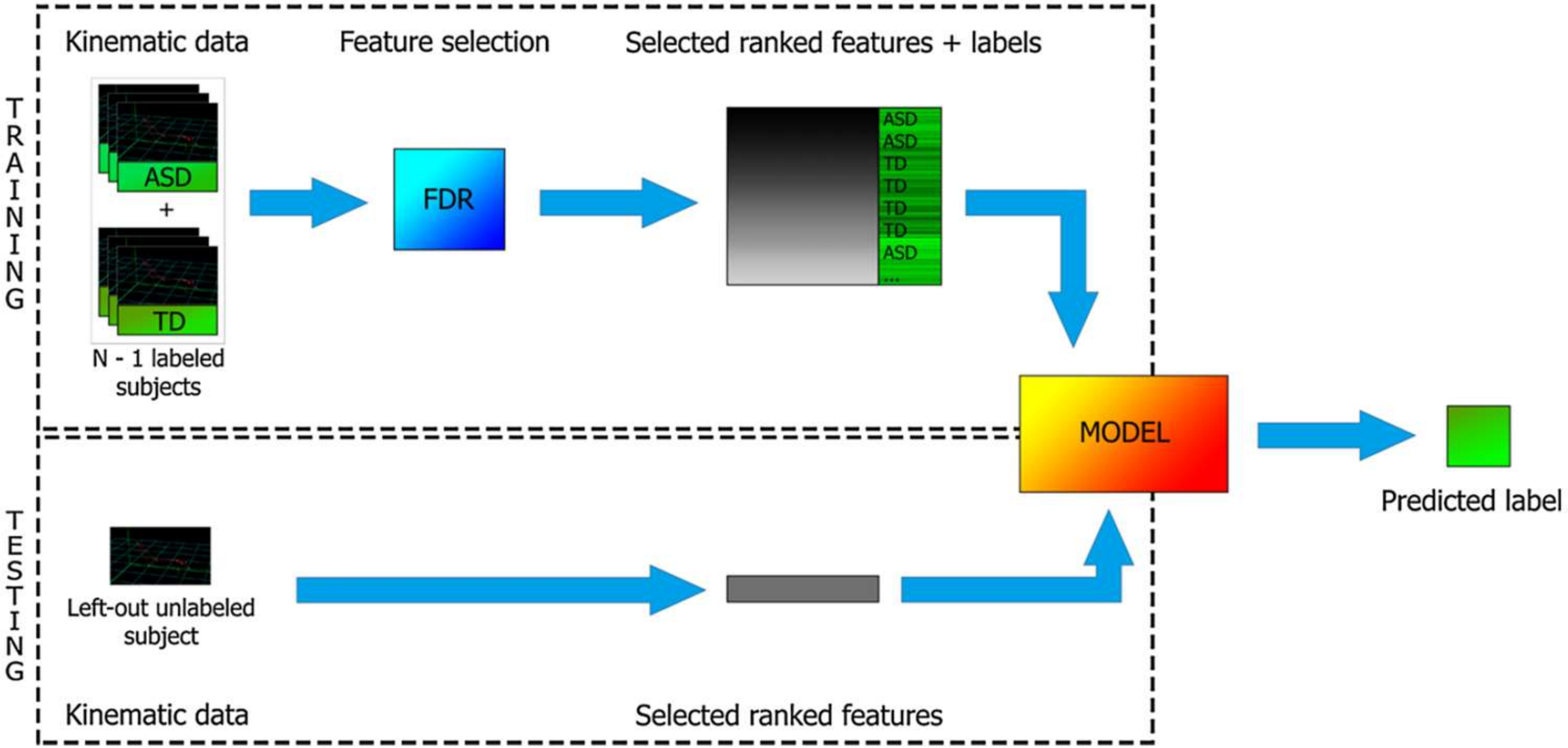
ML models | Examples



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ML models | Examples

	Overall mean	Optimal configuration
Diagnostic accuracy (sensitivity / specificity)	85 (82/ 89)%	97 (100/ 94)%

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ML models | Examples

	Overall mean	Optimal configuration
Diagnostic accuracy (sensitivity / specificity)	85 (82/ 89)%	97 (100/ 94)%

7 optimal features out of 17

sub-movement 2

the movement to transport the ball from a support to the target hole in which the ball was to be dropped

1. total movement duration
2. delta wrist angle
3. # movement units
4. time of peak deceleration
5. peak acceleration
6. time of peak velocity
7. peak velocity

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ML models | Examples

Attention-Deficit/Hyperactivity Disorder

Diagnosis of ADHD & Identification of a signature

22

TD

22

ADHD

A dataset of 44
school-aged children (~11 years old)

Multidomain profile of measures
. biological data
. neuropsychological data
. Near-InfraRed Spectroscopy (NIRS)

ADHD **Attention Deficit / Hyperactivity Disorder**
TD Typically-developing children

The Utility of a computerized algorithm Based on a Multi-Domain Profile of Measures for the Diagnosis of attention deficit/hyperactivity Disorder. *Crippa, Salvatore et al. 2017, Frontiers in Psychiatry.*

ML models | Examples

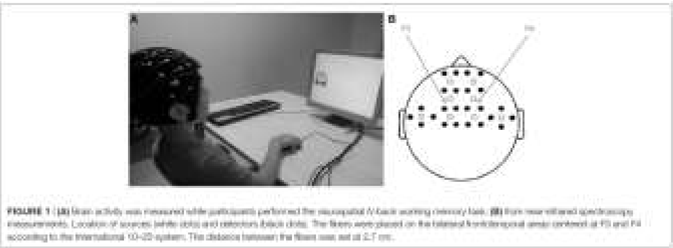
Multi-domain profile of measures

Biological data

10 features

Neuropsychological data

18 features



Near-InfraRed Spectroscopy (NIRS)

Oxy/Deoxy data from 32 channels

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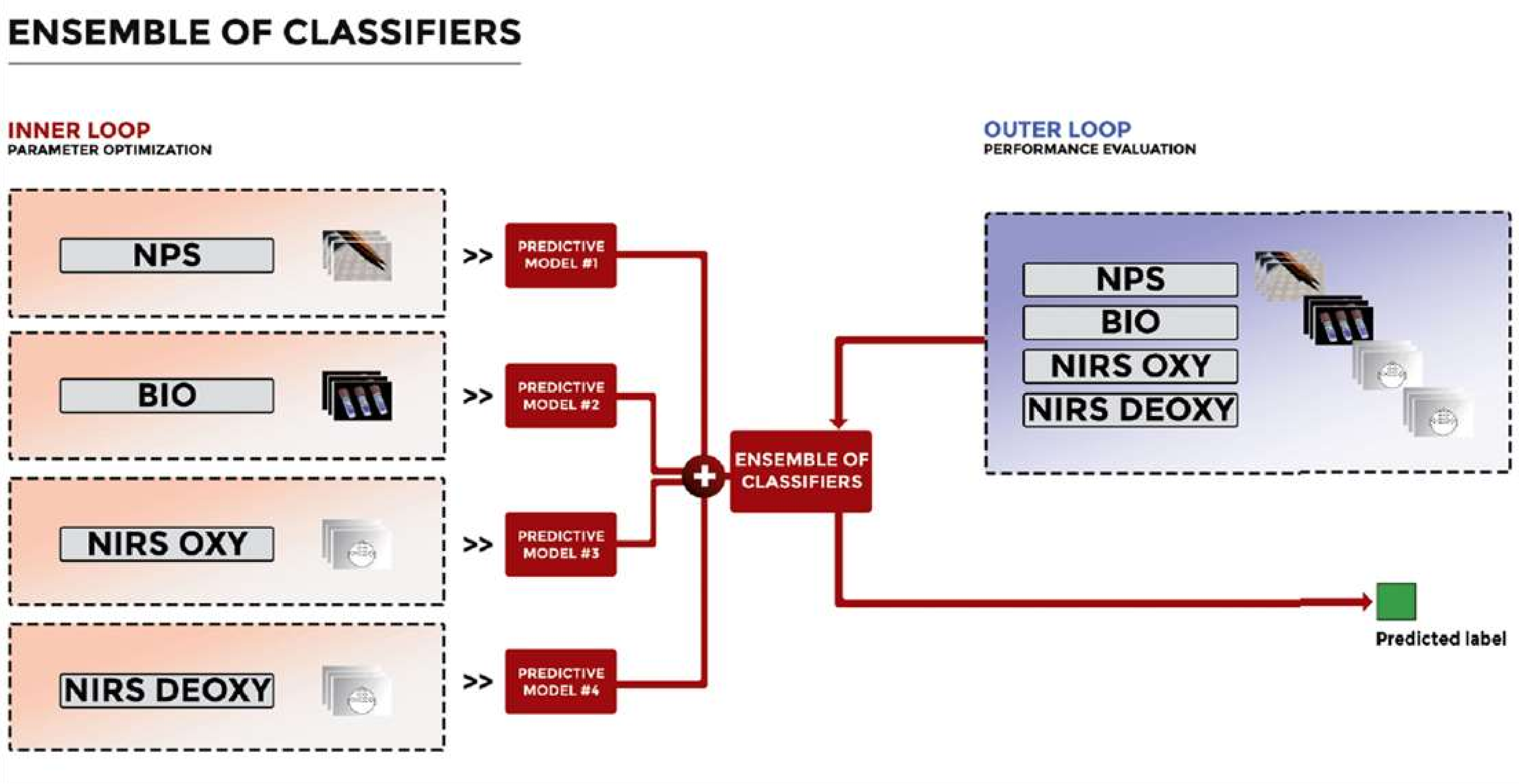
ML models | Examples



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ML models | Examples

Measures	Accuracy (mean ± sd)	Sensitivity (mean ± sd)	Specificity (mean ± sd)
Neuropsychological	62 ± 17	70 ± 27	57 ± 24
Biological	66 ± 21	58 ± 40	73 ± 29
NIRS OXY	57 ± 27	48 ± 47	67 ± 33
NIRS DEOXY	78 ± 22	72 ± 34	82 ± 24
NIRS OXY + DEOXY	72 ± 32	73 ± 29	68 ± 43

biological features

.linoleic acid
.PUFA
.AA
.EPA
.omega-3 index
.AA/DHA
.AA/EPA
.MUFA

linoleic acid and total amount of polyunsaturated fatty acids

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neuropsychological features

.***sustained attention***-*false alarms*
.***visual set***-*shifting-RT inhibition*
.*sustained attention-coefficient of variation*
.*visual set-shifting-number of inhibition errors*
.***focused attention***-*RT correct responses*
.*focused attention-correct rejections target non-relevant position*
.*focused attention-SD of correct responses RT*
.*focused attention-misses*
...

measures of vigilance, focused and sustained attention, and cognitive flexibility

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ML models | Examples

Single domain

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Multi-domain

Measures	Accuracy (mean ± sd)	Sensitivity (mean ± sd)	Specificity (mean ± sd)
NPS + BIO + NIRS OXY			
NPS + BIO + NIRS DEOXY			
NPS + NIRS OXY + NIRS DEOXY			
BIO + NIRS OXY + NIRS DEOXY			
NPS + BIO + NIRS OXY + NIRS DEOXY			

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ML models | Examples

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Multi-domain

Measures	Accuracy (mean ± sd)	Sensitivity (mean ± sd)	Specificity (mean ± sd)
NPS + BIO + NIRS OXY	71 ± 10	70 ± 27	73 ± 24
NPS + BIO + NIRS DEOXY	81 ± 15	73 ± 24	87 ± 22
NPS + NIRS OXY + NIRS DEOXY	78 ± 18	70 ± 36	87 ± 22
BIO + NIRS OXY + NIRS DEOXY	77 ± 21	63 ± 31	90 ± 21
NPS + BIO + NIRS OXY + NIRS DEOXY	76 ± 16	83 ± 22	68 ± 23

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