Manejo del paciente con ictus mediante una estrategia automatizada basada en aprendizaje automático

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¿preguntas clínicas?

-> ESTUDIO INTRAHOSPITALARIO

PREDICCIÓN - DIAGNÓSTICO

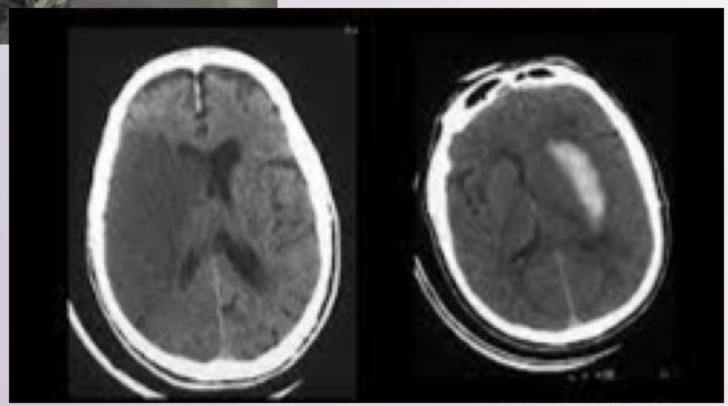
MORTALIDAD

COMPLICACIONES

RECURRENCIA

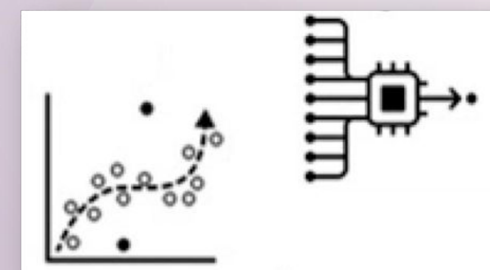
ISQUEMIA
vs
HEMORRAGIA

OCLUSIÓN DE
GRAN VASO

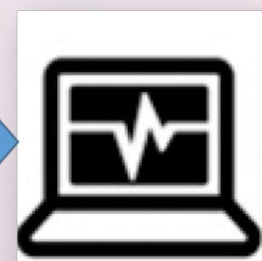


ESTUDIO PREDICCIÓN COMPLICACIONES FASE AGUDA INTRAHOSPITALARIA

Monitorización de variables UI



Procesamiento de datos
Modelamiento estadístico/algoritmo
Predicción



Propuesta resolutiva

Implementación

¿diagnóstico de oclusión de gran vaso?

-> **ESTUDIO EXTRAHOSPITALARIO**

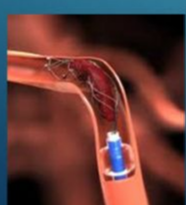
escala MADRID DIRECT

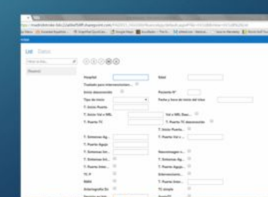
CÓDIGO ICTUS

ciudad de madrid
S.A.M.U.R.
PROTECCION CIVIL

MADRID
STROKE
network

SaludMadrid
SUMMA 112
Comunidad de Madrid





"LA SUMA DE TODOS"

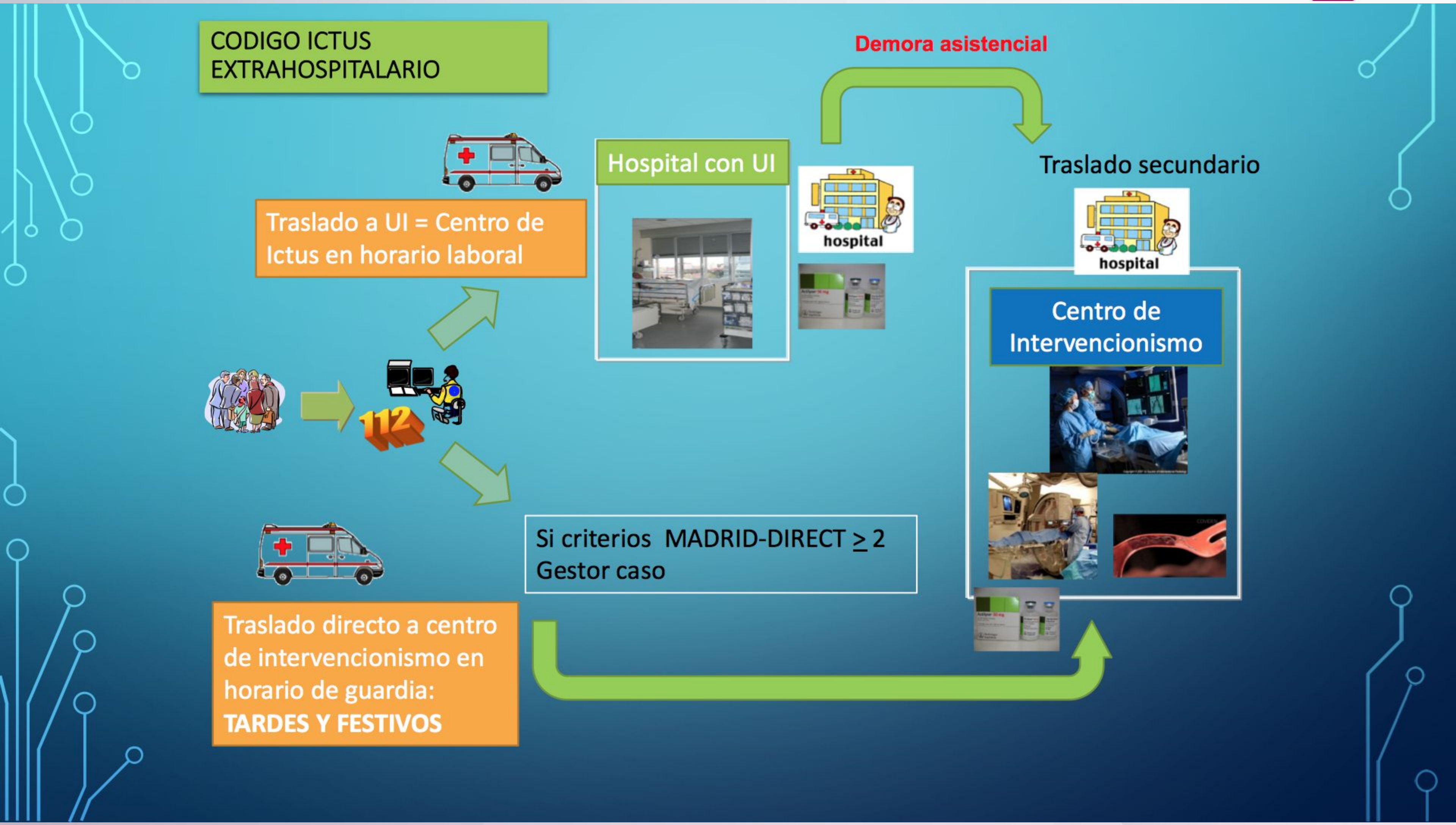
SISTEMA ORGANIZATIVO

- Hospitales sin Unidad de Ictus
- **Unidades de Ictus**
  - 10 % hemorragias
  - 10 % no vasculares
  - Trombolisis iv
  - Trombectomía mecánica
- **Centros de Ictus 8-15h**

Demora asistencial

- **Centros de guardia Neurointervencionismo**

Gestor caso
SAMUR 13.1
MADRID-DIRECT


CODIGO ICTUS EXTRAHOSPITALARIO
Demora asistencial
Hospital con UI
hospital
Traslado secundario
hospital
Traslado a UI = Centro de Ictus en horario laboral
Centro de Intervencionismo
112
Si criterios MADRID-DIRECT ≥ 2
Gestor caso
Traslado directo a centro de intervencionismo en horario de guardia:
TARDES Y FESTIVOS

PUBLIC

PREDICTIVE

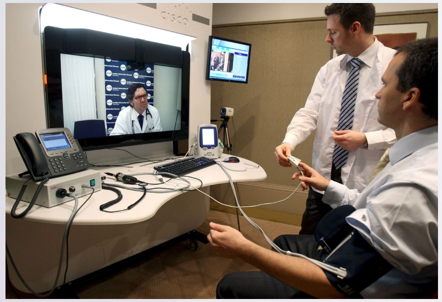
PERSONALIZED

The P6 Medicine

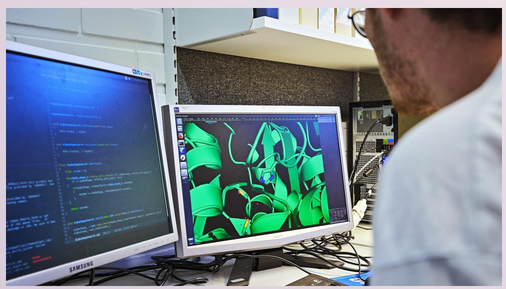
PREVENTIVE

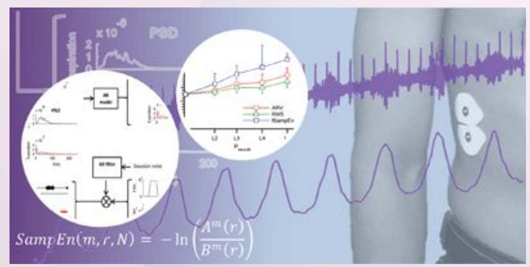
PSYCHOSOCIAL

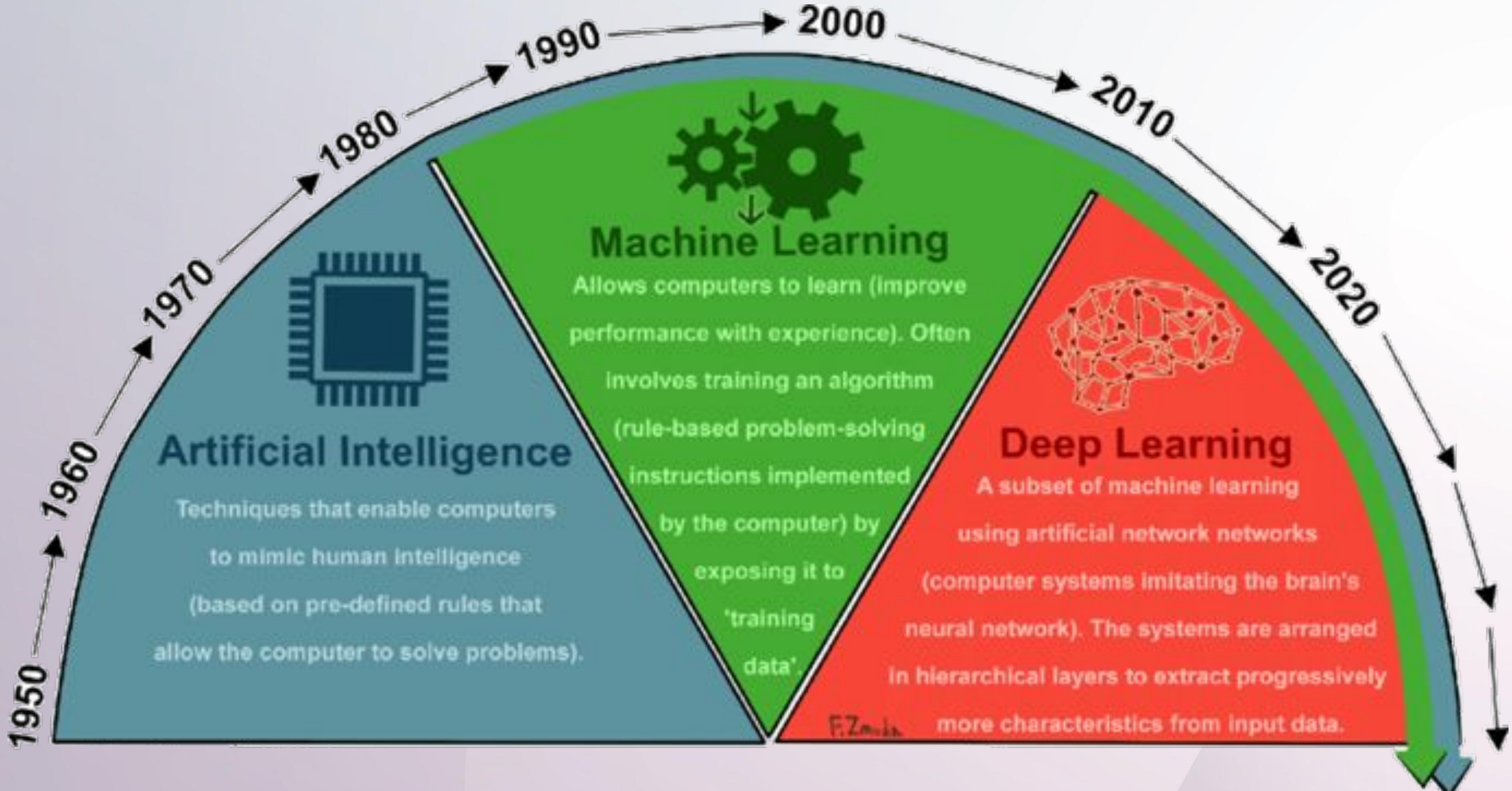
PARTICIPATORY



Bioengineering
&
Biocomputing

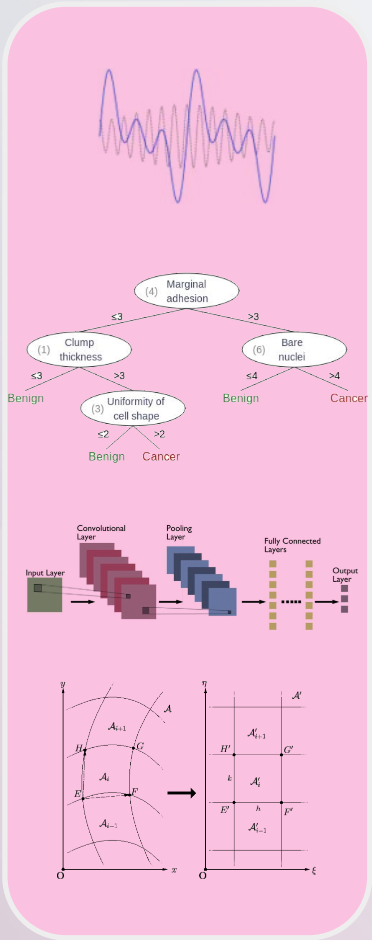






1950
1960
1970
1980
1990
2000
2010
2020
Artificial Intelligence
Techniques that enable computers to mimic human intelligence (based on pre-defined rules that allow the computer to solve problems).
Machine Learning
Allows computers to learn (improve performance with experience). Often involves training an algorithm (rule-based problem-solving instructions implemented by the computer) by exposing it to 'training data'.
Deep Learning
A subset of machine learning using artificial network networks (computer systems imitating the brain's neural network). The systems are arranged in hierarchical layers to extract progressively more characteristics from input data.

From a data engineering perspective



Automatic Diagnosis

Prediction of events

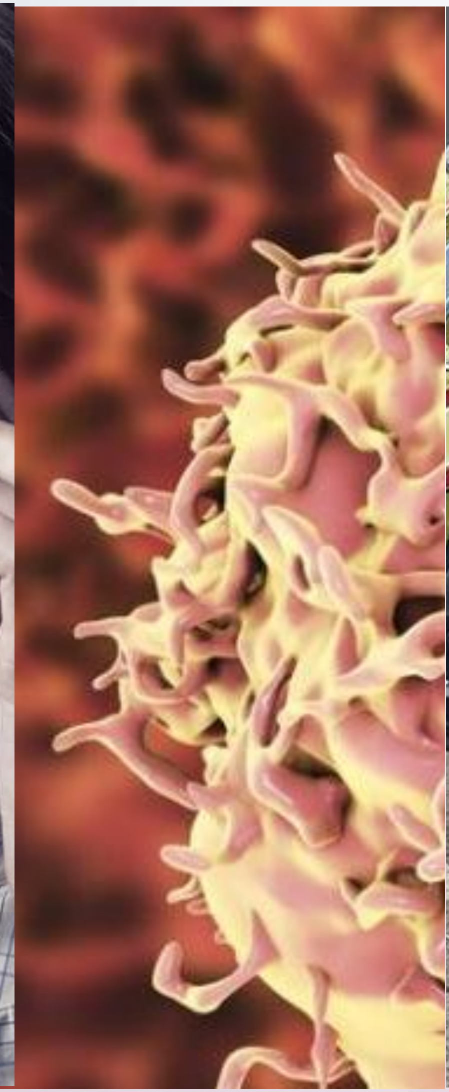
Treatment Personalization

Real-time tools

mHealth

Cloud services





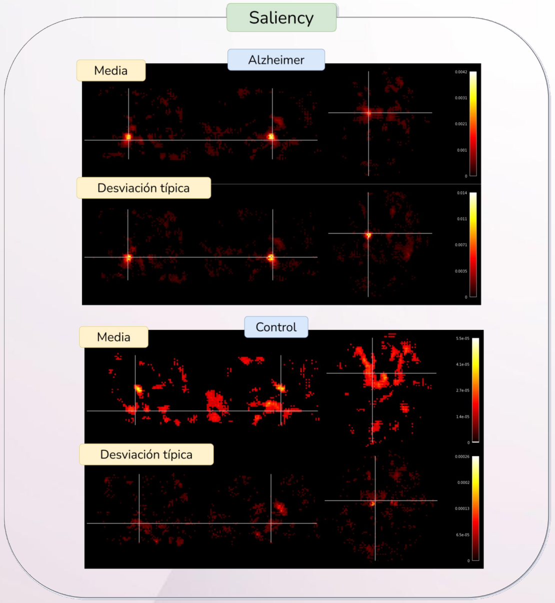

Dementia

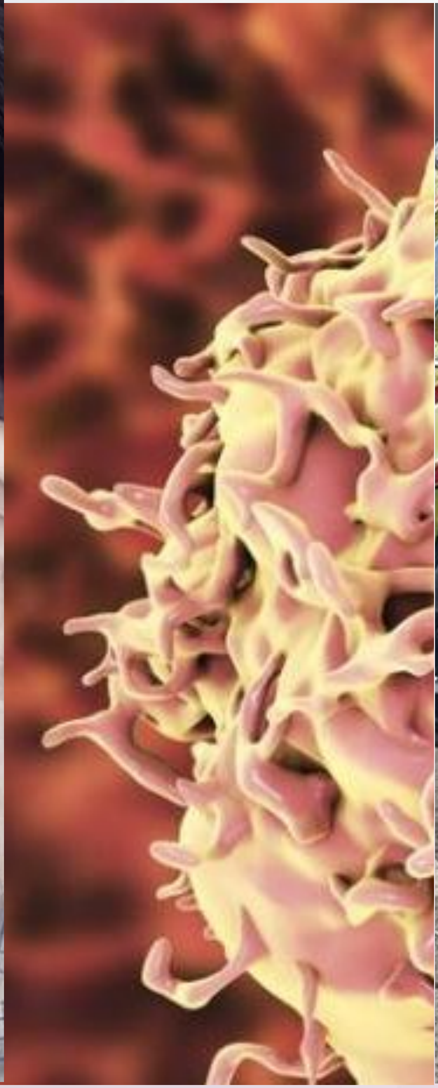
Automatic diagnosis
Prediction of evolution
Treatment personalization

Data: neuroimages, genomics, cognitive assessment data, EEG, biomarkers.

Deep learning techniques for **PET and tau-PET,** interpretability, temporal models from blood **biomarkers**, graph neural networks for **PPI**, evolutionary feature selection from cognitive tests, personalized **TMS** protocol from **EEG** data

4 clinical trials, more than 10 Q1 journal papers, 3 PhD thesis





Migraine

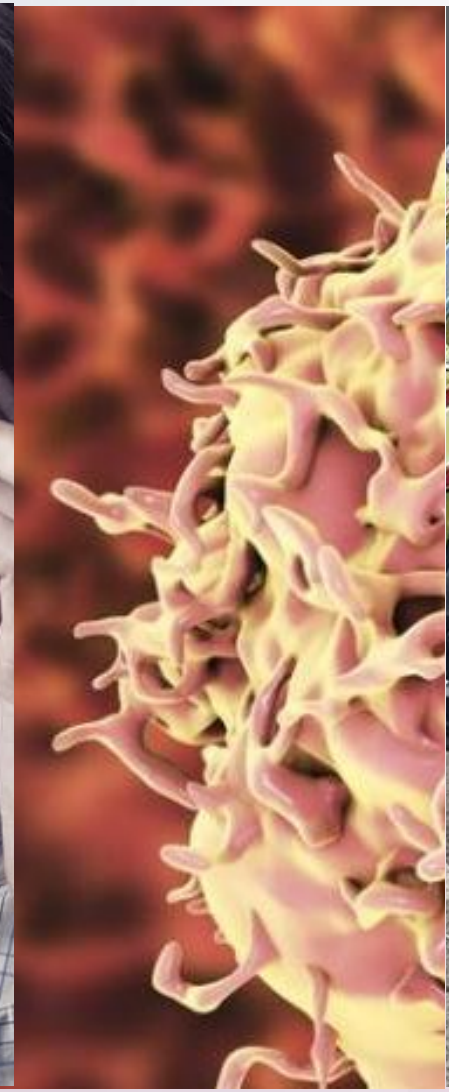
Prediction of pain
Treatment personalization
Patient profiling

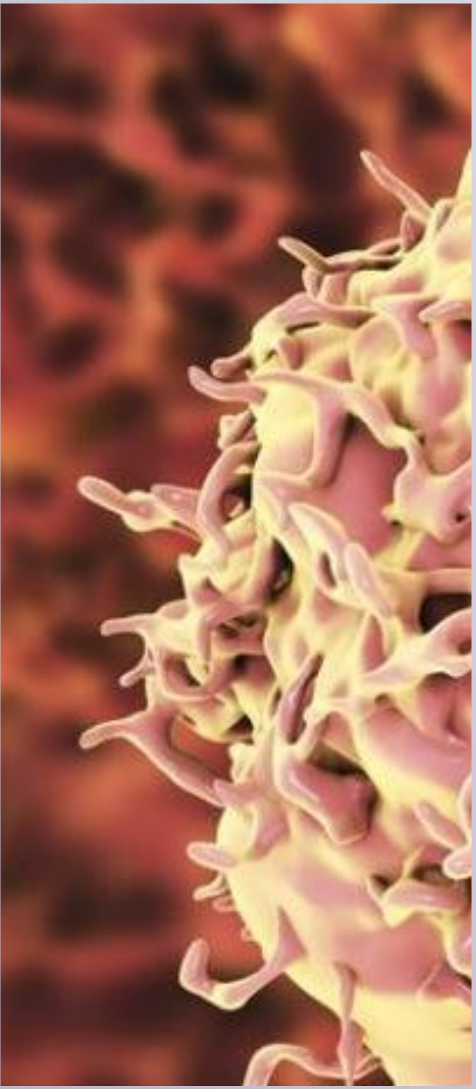
Data: ambulatory hemodynamic data, blood biomarkers, clinical scales, self-reported questionnaires, atmospheric variables.

Signal processing techniques for real-time data from **wearables**, **predictive** machine learning models, patient's **response** to Botox from blood tests, gamification techniques to improve **adherente** to apps, mHealth

3 clinical trials, 5 Q1 journal papers, 2 PhD thesis, 3 patents, 1 spin-off company, 10 innovation awards





Cancer

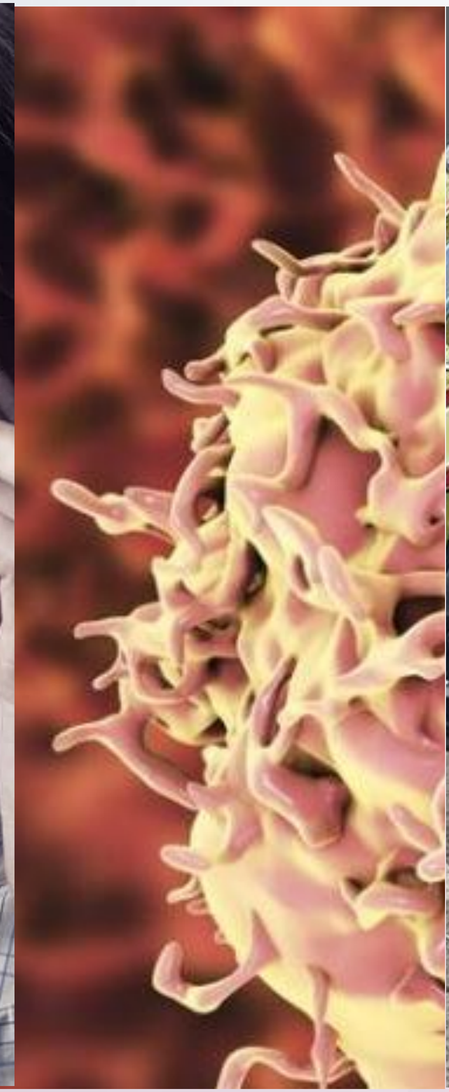
Treatment personalization
Prediction of pain

Data: ambulatory hemodynamic data, blood biomarkers, clinical scales, RNA sequencing

Deep learning techniques for **immunotherapy** and **chemotherapy personalization**, signal processing techniques for **real-time** data from wearables, **predictive** machine learning models, **mHealth**

2 clinical trials, 1 Q1 journal paper, 1 patent, 1 national large-scale consortium



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Stroke

Automatic diagnosis
Prediction of evolution
Treatment personalization

Data: hemodynamic data, clinical scales, clinician's feedback.

Machine learning models for automatic **subtype diagnosis**, and **prediction** of events (exitus, bleeding), real-time **recommender** systems to support acute **treatment** decisions.

1 in-hospital clinical trial, 1 out-of-hospital clinical trial, 2 Q1 journal papers, 2 PhD thesis, 1 national large-scale cooperative network, 1 running demonstrator

Table 9: Stroke diagnosis model: performance metrics

Perf. metric	DTW	Nearest Neighbour	Gradient Boost	Random Forests	Decision Tree
Sensitivity	0.8736	0.9134	**0.9783**	0.9567	0.8881
Specificity	0.9509	0.9701	**0.9957**	0.9893	0.9594
F-Measure	0.8930	0.9301	**0.9855**	0.9689	0.9077
Accuracy	0.9221	0.9490	**0.9893**	0.9772	0.9329
ROC Area	0.9123	0.9417	**0.9870**	0.9730	0.9237
PRC Area	0.9169	0.9794	**0.9994**	0.9975	0.9290
Avg	0.9115	0.9473	**0.9892**	0.9771	0.9235

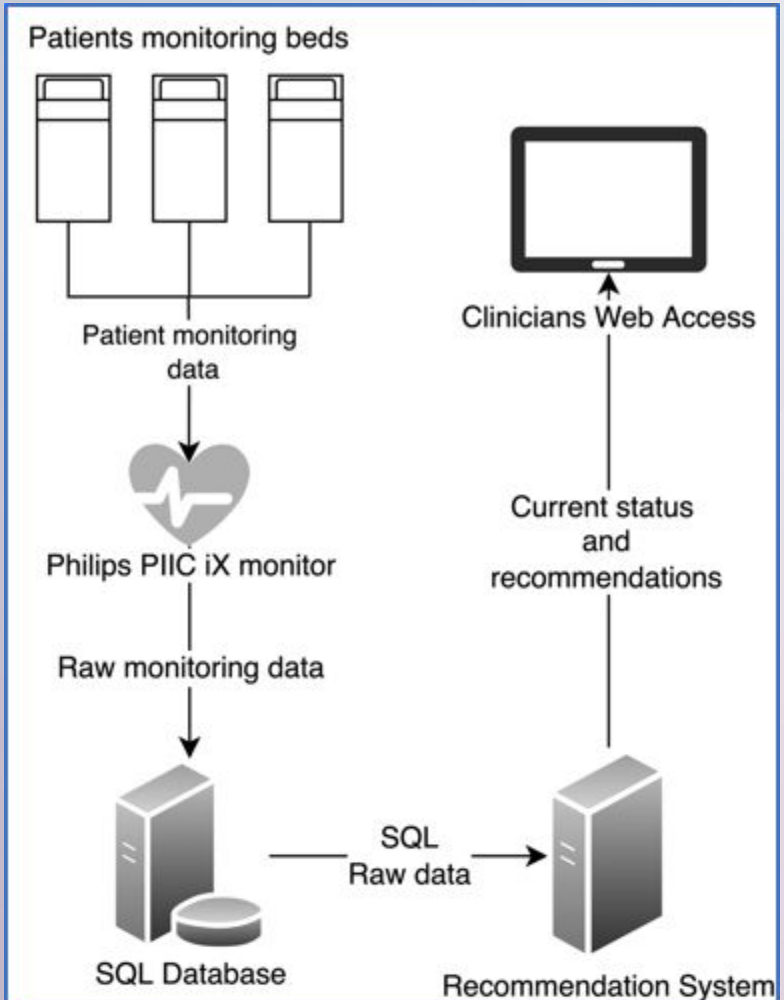
Table 10: Exitus prediction: performance metrics

Perf. metric	DTW	Nearest Neighbour	GradientBoost	AdaBoost	Random Forests
sensitivity	0.8757	0.9416	**0.9981**	0.9718	0.9812
Specificity	0.9407	0.9844	0.9990	0.9825	**1.0000**
F-Measure	0.8798	0.9551	**0.9981**	0.9690	0.9905
Accuracy	0.9185	0.9699	**0.9987**	0.9788	0.9936
ROC Area	0.9082	0.9630	**0.9986**	0.9771	0.9906
PRC Area	0.9010	0.9836	**1.0000**	0.9940	0.9999
Avg	0.9040	0.9663	**0.9988**	0.9789	0.9926

Table 11: Stroke recurrence prediction: performance metrics

Perf. metric	DTW	Nearest Neighbour	GradientBoost	AdaBoost	Random Forests
Sensitivity	0.9231	0.9038	0.9231	**0.9808**	**0.9808**
Specificity	**0.9896**	0.9792	0.9583	0.9375	**0.9896**
F-Measure	0.9505	0.9307	0.9231	0.9358	**0.9808**
Accuracy	0.9662	0.9527	0.9459	0.9527	**0.9865**
ROC Area	0.9563	0.9415	0.9407	0.9591	**0.9852**
PRC Area	0.9648	0.9841	0.9892	0.9919	**0.9993**
Avg	0.9584	0.9487	0.9467	0.9596	**0.9870**

ESTUDIO INTRAHOSPITALARIO predicción



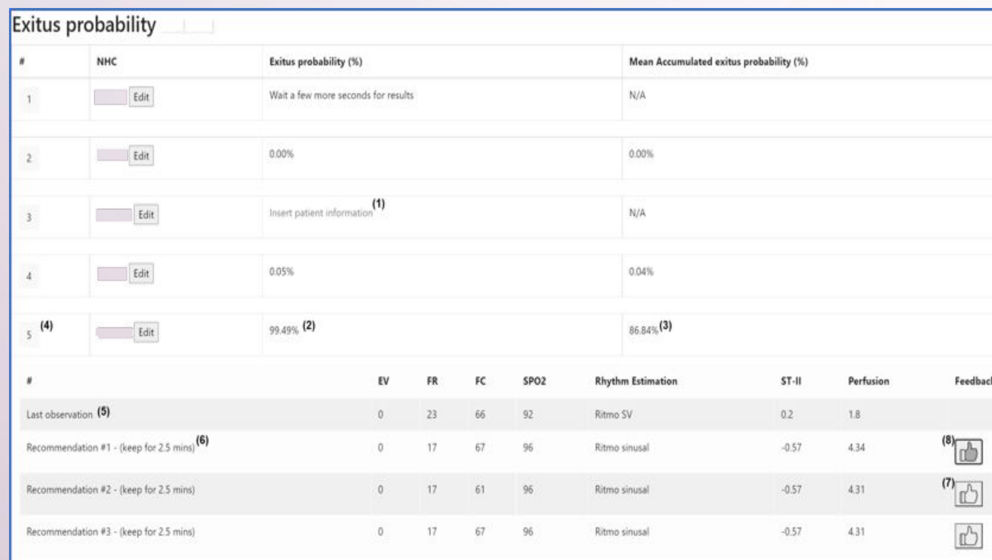
Patient [redacted]

Age

Gender ○ Male ○ Female

Stroke type ○ Ischaemic ○ Hemorrhagic ○ Mimic Stroke

Submit



Exitus probability

#	NHC	Exitus probability (%)	Mean Accumulated exitus probability (%)
1	Edit	Wait a few more seconds for results	N/A
2	Edit	0.00%	0.00%
3	Edit	Insert patient information (1)	N/A
4	Edit	0.05%	0.04%
5 (4)	Edit	99.49% (2)	86.84% (3)

#	EV	FR	FC	SPO2	Rhythm Estimation	ST-II	Perfusion	Feedback
Last observation (5)	0	23	66	92	Ritmo SV	0.2	1.8	
Recommendation #1 - (keep for 2.5 mins) (6)	0	17	67	96	Ritmo sinusal	-0.57	4.34	(8)
Recommendation #2 - (keep for 2.5 mins)	0	17	61	96	Ritmo sinusal	-0.57	4.31	(7)
Recommendation #3 - (keep for 2.5 mins)	0	17	67	96	Ritmo sinusal	-0.57	4.31	

Exitus probability

#	NHC	Scheduled Admission	Exitus probability (%)	Mean Accumulated exitus probability (%)
1	Edit	False	Variable ST-II is not being monitored, the system is not able to calculate exitus probability	N/A
2	Edit	False	Variable ST-II is not being monitored, the system is not able to calculate exitus probability	N/A
3	Edit	False	Variable EV is not being monitored, the system is not able to calculate exitus probability	99.98%
4	Edit	False	32.46%	25.01%

ESTUDIO INTRAHOSPITALARIO recomendador

Exitus probability

#	NHC	Exitus probability (%)	Mean Accumulated exitus probability (%)
1	Edit	Wait a few more seconds for results	N/A
2	Edit	0.00%	0.00%
3	Edit	Insert patient information (1)	N/A
4	Edit	0.05%	0.04%
5 (4)	Edit	99.49% (2)	86.84% (3)

#	EV	FR	FC	SPO2	Rhythm Estimation	ST-II	Perfusion	Feedback
Last observation (5)	0	23	66	92	Ritmo SV	0.2	1.8	
Recommendation #1 - (keep for 2.5 mins) (6)	0	17	67	96	Ritmo sinusal	-0.57	4.34	(8)
Recommendation #2 - (keep for 2.5 mins)	0	17	61	96	Ritmo sinusal	-0.57	4.31	(7)
Recommendation #3 - (keep for 2.5 mins)	0	17	67	96	Ritmo sinusal	-0.57	4.31	

ESTUDIO INTRAHOSPITALARIO recomendador

Exitus probability

#	NHC	Exitus probability (%)	Mean Accumulated exitus probability (%)
1	Edit	Wait a few more seconds for results	N/A
2	Edit	0.00%	0.00%
3	Edit	Insert patient information (1)	N/A
4	Edit	0.05%	0.04%
5 (4)	Edit	99.49% (2)	86.84% (3)

#	EV	FR	FC	SPO2	Rhythm Estimation	ST-II	Perfusion	Feedback
Last observation	0	24	81	100	Ritmo sinusal	1.5	0.58	
Recommendation #1 - (keep for 2.5 mins)	0	20	64	100	Fib/Taqui Vent	-3.47	2.53	
Recommendation #2 - (keep for 2.5 mins)	0	25	138	99	Ritmo vent.	-0.38	6.63	
Recommendation #3 - (keep for 2.5 mins)	0	36	107	98	Trigemin. vent.	-2.1	16.36	

ESTUDIO EXTRAHOSPITALARIO

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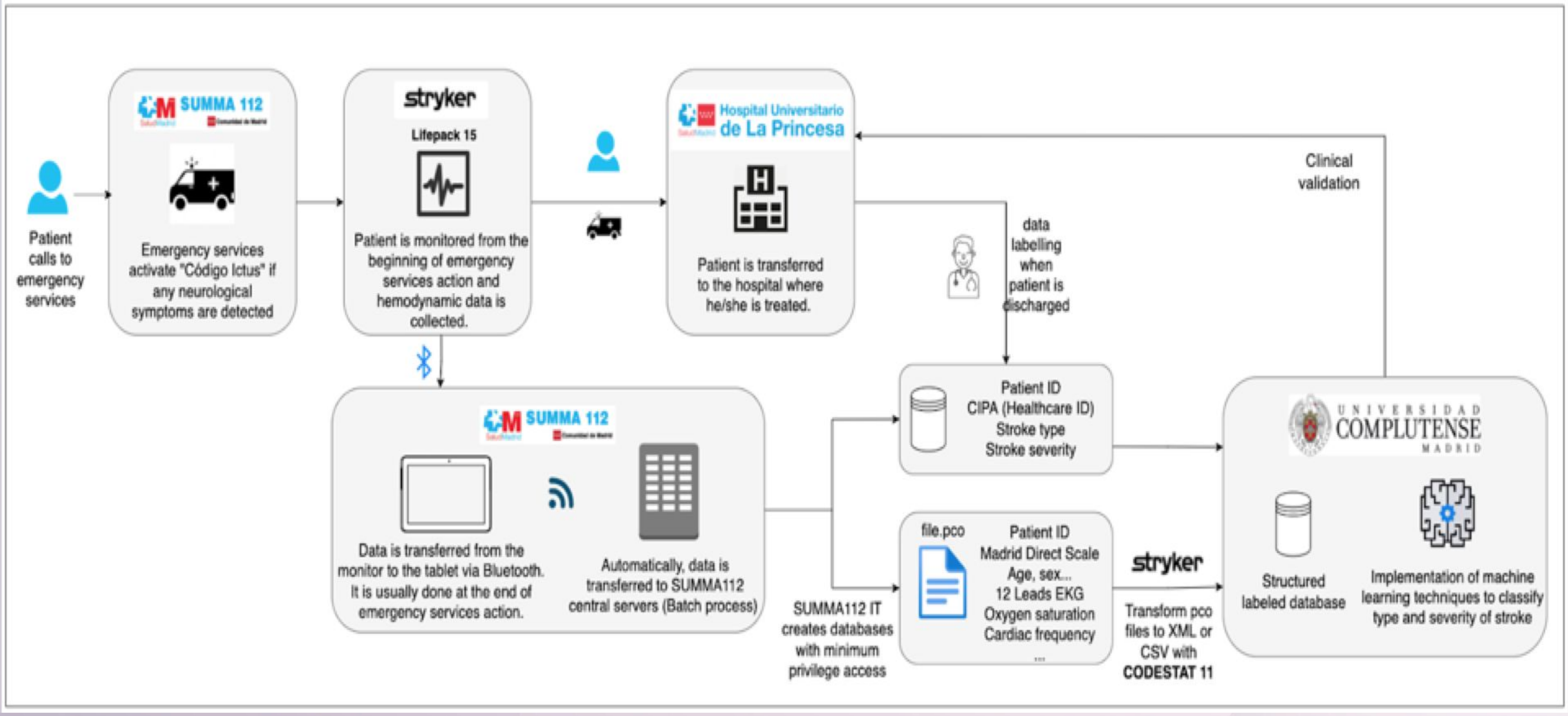
DETECTAR OCLUSIÓN DE GRAN VASO

ESTUDIO EXTRAHOSPITALARIO



Hospital Universitario La Paz

Hospital Universitario Ramón y Cajal

Hospital Universitario 12 de Octubre

estado actual

INTRAHOSPITALARIO

- refinamiento modelos de predicción establecidos (diagnóstico y pronóstico)
- búsqueda y validación de nuevos modelos de predicción
- puesta en marcha recomendador

EXTRAHOSPITALARIO

- estableciendo el flujo de datos clínicos y hemodinámicos, así como su ETIQUETADO de forma fluida y dinámica
- PREPARADOS PARA ANALIZAR

conclusiones

- Es posible **diagnosticar** (hemorragia vs isquemia) y **predecir complicaciones** en la fase aguda del ictus con datos de monitorización mediante técnicas de aprendizaje automático en un medio "controlado" de monitorización

- Diseño y puesta en marcha **SISTEMA RECOMENDADOR** para evitar complicaciones neurológicas fase aguda.

- Confirmar que es posible en el ámbito extrahospitalario - diagnóstico de OCLUSIÓN DE GRAN VASO

ABIERTOS A COLABORAR…