ERN | EuroBloodNet

13th June 2025 - EHA Congress

Radiomics in Sickle Cell Disease

Speaker: Raffaella Colombatti, AO Padova

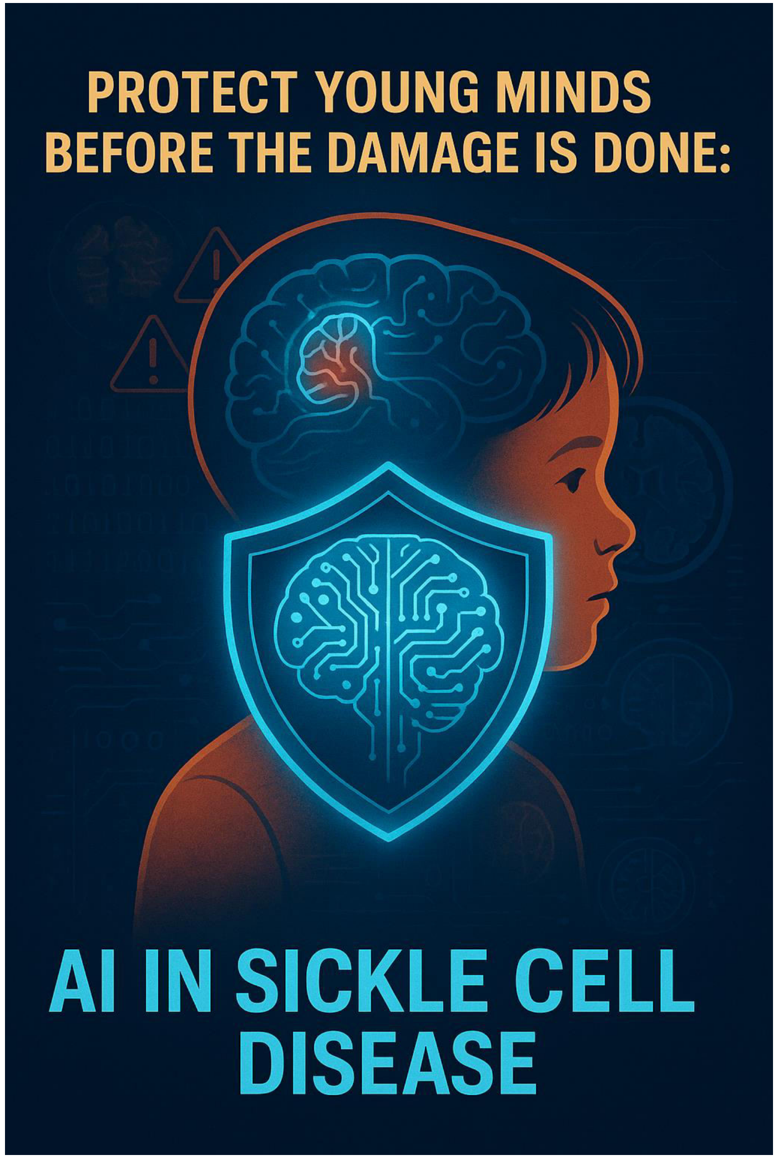
European Reference Network | Hematological Diseases (ERN EuroBloodNet)

Funded by the European Union

Disclosure of Conflict of Interest

Advisory Board/Consultancy: NovoNordisk, Vertex, Pfizer, Agios
Research Funding: Vertex, Agios

Protect young minds before the damage is done: AI in SCD



Artificial intelligence aims

- Aim 1) Omics-based classification and prognosis of SCD
  - to develop personalized predictive models for patients with SCD through integration of comprehensive genomic clinical information
- Aim 2) AI model to predict risk scores and time of ocurrence for:
  - Recurrent Vaso Occlusive Crisis
  - Acute chest syndrome
  - Cerebral Silent Infarcts
  - *Stroke (<20%)*
  - *Renal disease (<20%)*
  - *Hepatic failure (<20%)*
- **Aim 3) AI based radiomics for imaging diagnosis of cerebral silent infarct**
- Aim 4) Development of AI models for synthetic data generation – Augmentation
  - Increase categories e.g. stroke
  - External control arms in clinical trials

RADeep

GENOMED4ALL

SYNTHEMA

European Reference Network | Hematological Diseases (ERN EuroBloodNet)
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Specific AIMS

1) IDENTIFY SCI AND DISTINGUISH IT FROM OTHER LESION

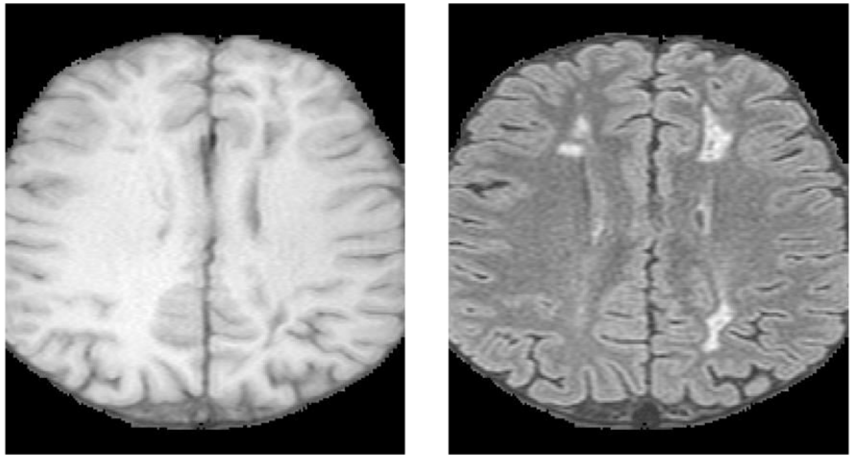
2) PREDICTION OF RISK OF DEVELOPING SCI IN THE FUTURE

Results

AI based radiomics for imaging diagnosis of cerebral silent infart (CSI)

MRI Exam Composition

- T1 Weighted
- FLAIR (3D or 2D Axial)



1.Anonymized MRI Dataset preparation (2022)

- 541 MRIs
- 225 ABNORMAL REPORT (Cerebral Silent Infarct)
- 70% PEDIATRIC
- 7 centers
  - NA, MO, TO, PD, GE Italy
  - VHIR Barcelona
  - UMC Amsterdam
- Philips 1.5 T (n.2), Siemens 1.5 T and 3 T (n.2), GE 3T (n.3)

Results

2. Implemented Pipeline to define and train the algorithm on MRI (2022-2023)

NEURORADIOLOGIST

AI EXPERTS

Image without label

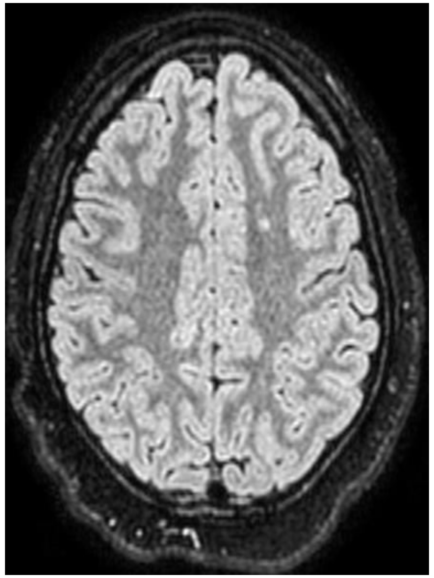
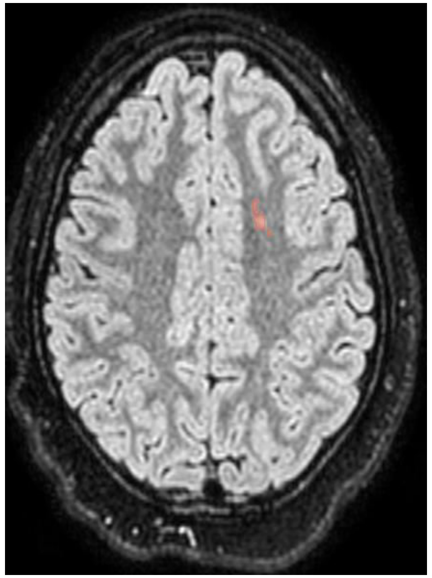
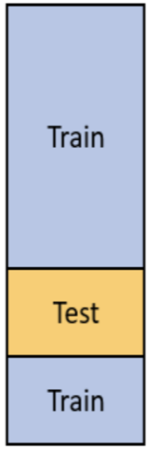


Image with label



First semi automatic SCI IDENTIFICATION with the algorithm -3 deep learning models (pre-processing – WMH segmentation – post processing) in a subset

TRAINING on a 1st set of MRIs



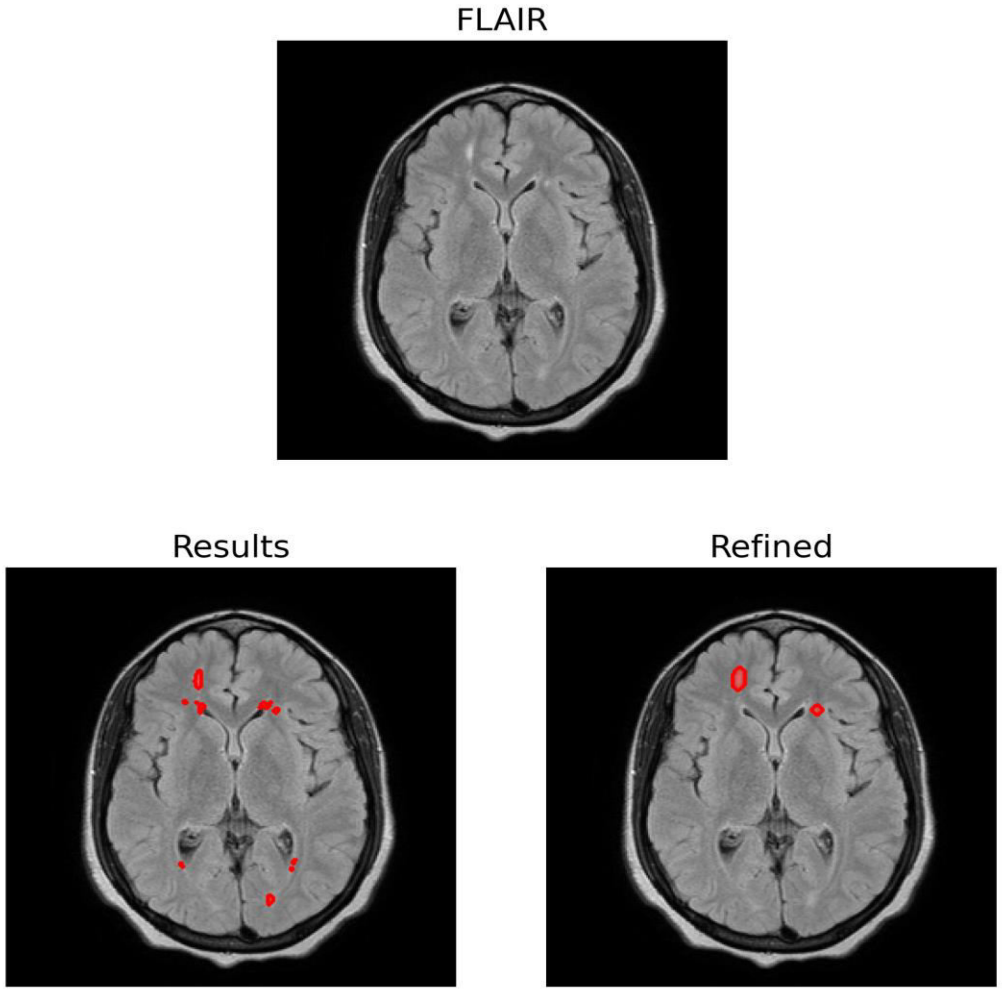
AI EXPERTS

LABELING OF each single MRI exam after the algorithm identified the SCI

REFINING SEGMENTATION manually (NR) : second training of NEURAL NETWORK with «correct labeling»

RETRAINING on more MRIs

3.Testing the algorithm on a different set of MRIs (2023-2024)



- The images approved, were used to increase the dataset to retrain the model. The retraining part used the Marconi100 supercomputer kindly provided by CINECA.
- Testing on a different dataset from the one that was used for training
- Blind review of a sample of MRIs by 3 neuroradiologists to check for consistency in diagnosis and categorization of lesions (Padova, Barcelona, Amsterdam)

Automated Identification of Silent Cerebral Infarcts in Sickle Cell Disease: A Multicenter European Study Reflecting Real-World Variability

Riccardo Biondi[1], Maria Paola Boaro[2], Nicolas Biondini[3], Anna Collado Gilbert[4], Escudiero Fernandez JM[5], Valeria Pinto[6], Nicola Romano[7], Vincenzo Voi[8,9], Giovan Battista Ferrero[8], Maddalena Casale[10], Mario Cirillo[11], Gian Luca Forni[6], Giulia Reggiani[2], Silverio Perrotta[10], María del Mar Mañú Pereira[12], Sara Reidel[12], Santiago Zazo[13], Mariane De Montalembert[14], Bart J. Biemont[15], Pablo Bartolucci[16], Eduard Van Beers[17], Federico Alvarez[18], Francesco Cremonesi[19,20], Cesare Rollo[21], Tiziana Sanavia[21], Piero Fariselli[21], Gastone Castellani[3,22], Renzo Manara[23], Raffaella Colombatti[2]

Manuscript will be submitted next week

4.Preliminary evaluation of correlation of clinical/ematological parameters to MRIs results (2024-2025)

Federated Learning for SCD real data to predict Silent Cerebral Infarction

Binary target data:

presence/absence of SCI, completely defined by means of the real MRI outcomes.

Input data:

- Clinical variables: ALT, AST, direct, indirect and total bilirubin, creatinine, ferritin, GB, LDH, urea
- Physical parameters: blood pressure, oxygen saturation, weight, height, heart rate
- Time intervals: days corresponding to the date the values were recorded and the date of SCI

Federated Learning environment with small datasets:

Node1	Node2	Node3	Test
27 samples	15 samples	10 samples	13 samples

Federated Learning model:

Logistic Regression predicts presence/absence of SCI, with class balance and L2-penalty

It meets the simplicity requirements for the initial platform tests.

Experimenting Federated AI Models for Hematological Diseases

Luciana Carota[1][0000−0002−9217−4600], Francesco Casadei[2][0009−0006−0789−546X],
Gianluca Asti[3][0009−0006−9078−6482], Davide Piscia[4][0000−0002−0468−0408],
Patricia A. Apellániz[5][0000−0002−8604−9758], Savi
D'Amico[3][0000−0003−1877−8497], Riccardo Biondi[2][0000−0002−86
Sala[1][0000−0003−4031−4648], Nono S.C. Merleau[5][0000−0003−3150-
van Deventer[6][0000−], Raffaella Colombatti[7][0000−0001−9797−
Mezzalira[7][0000−0003−0486−0342], Stefano Polizzi[1][0000−0002−
Peluso[1][0000−0003−1924−1093], Cesare Rollo[8][0000−0001−6093−
Sanavia[8][0000−0003−3288−0631], Piero Fariselli[8][0000−0003−1811
Zazo[5][0000−0001−9073−7927], Juan Parras[5][0000−0002−7028−3179
Porta[3][0000−0002−6915−5970], Federico Alvarez[5][0000−0001−7400−9591], Gastone
Castellani[1,10][0000−0003−4892−925X], and Enrico
Giampieri[1,10][0000−0003−2269−2338]

1st Workshop on Artificial Intelligence for Biomedical Data (AIBio) 2025

Results

1) The identification model of silent infarct lesions:

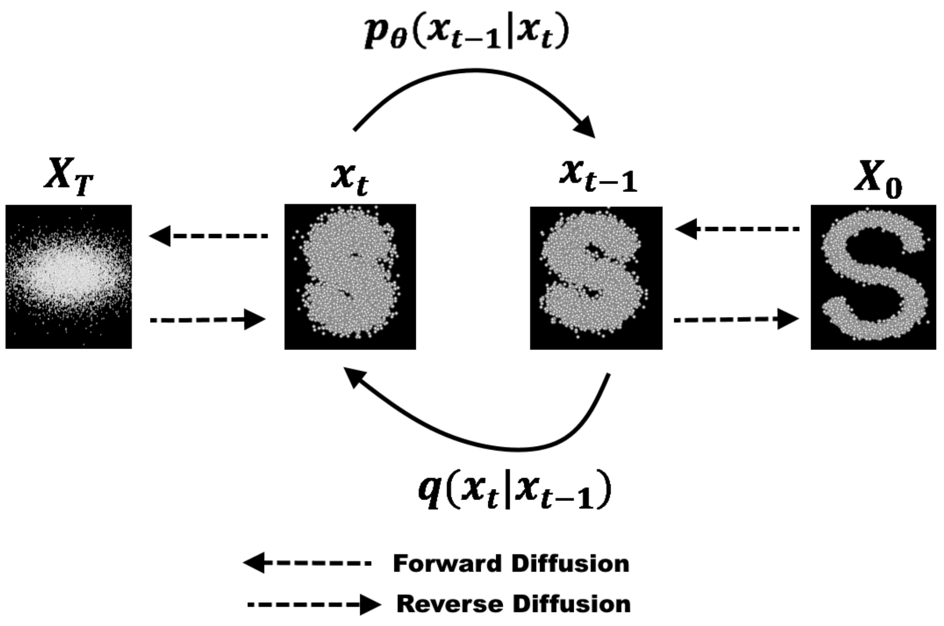
- Clinical Decision Support System (CDSS) = will reduce diagnosis time especially in non-expert centers and reduce diagnostic errors.
- It will improve the monitoring of the child to detect neurocognitive deterioration early, thus applying interventions early and preventively, different strategies (e.g. neurocognitive therapy, school reinforcement...)

2) The predictive risk score would represent a significant improvement in patient stratification

- would improve clinical decision-making regarding bone marrow transplantation/gene therapy or new disease-modifying therapies
- would help personalize and adjust monitoring and prevention strategies for chronic organ damage.

Synthetic Images Generation-State of the Art

- High-quality and photorealistic image outputs
- Capable of generating diverse and creative visuals
- Strong performance on complex prompts and fine details



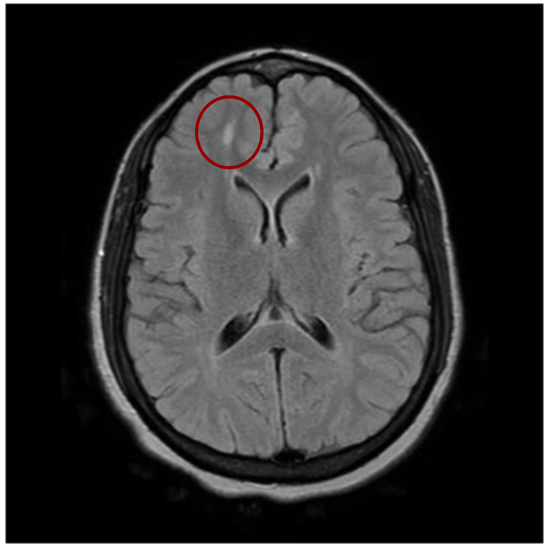
- Computationally expensive and slow to generate images
- Requires large datasets and resources for training
- May produce biased or inappropriate content without safeguards

Khader, F., Mueller-Franzes, G., Arasteh, S. T., Han, T., Haarburger, C., Schulze-Hagen, M., ... & Truhn, D. (2022). Medical Diffusion--Denoising Diffusion Probabilistic Models for 3D Medical Image Generation. *arXiv preprint arXiv:2211.03364*.

Slides from Gastone Castellani

Sickle Cell Disease

FLAIR and T1 MRI Exams with presence of Silent Cerebral Infarction. Extraction of radiomic features from the lesion areas

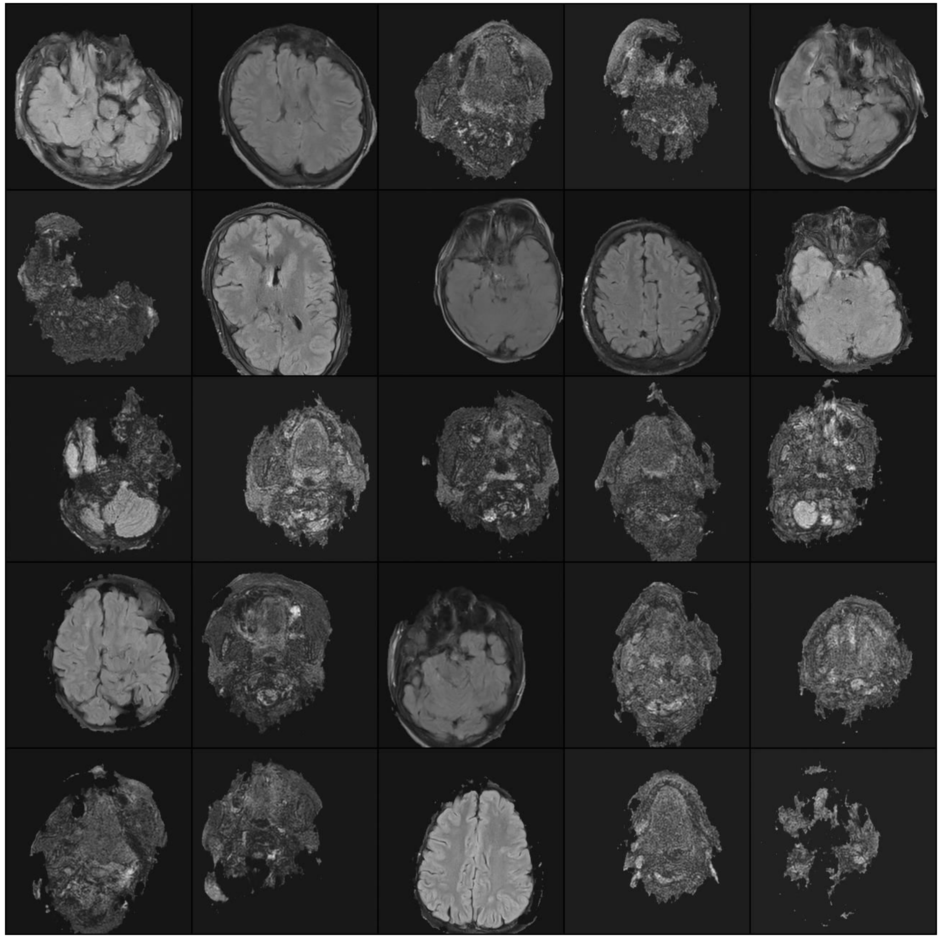


Outline

- **Generate and Segment synthetic FLAIR and T1W images**
- **Generate directly synthetic radiomic features data**

Slides from Gastone Castellani

Results and Next Step



Current Work

- 2D FLAIR Generated Samples
- No Mask Generation
- No Accurate Evaluation

Next Steps

- Extend from 2D to 3D generation
- Silent Cerebral Inferction mask Generation
- Accurate Synthetic Data Validation

Slides from Gastone Castellani

Thanks to the Core MRI - Team

UNPD:
Maria Paola Boaro
Giulia Reggiani
Elisabetta Mezzalira
Renzo Manara
Silvia Valeggia

UNIBO:
Gastone Castellani
Riccardo Biondi
Nicolas Biondini
Luciana Carota

Thanks to the MRI Group

Torino Orbassano, Genova Galliera, Napoli Vanvitelli, Barcellona VHIR, Amsterdam-Utrecht, Paris

THANK YOU!

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