AI@INFN, Bologna, May 3rd, 2022

Using X-ray technologies and deep neural networks for digital restoration of paintings: the CHNet AIRES-CH project

Alessandro Bombini, *INFN Firenze*

more on chnet

INFN CHNet

4CH
COMPETENCE CENTRE FOR THE CONSERVATION OF CULTURAL HERITAGE

EOSC-Pillar
Coordination and Harmonisation of National &Thematic Initiatives to support EOSC

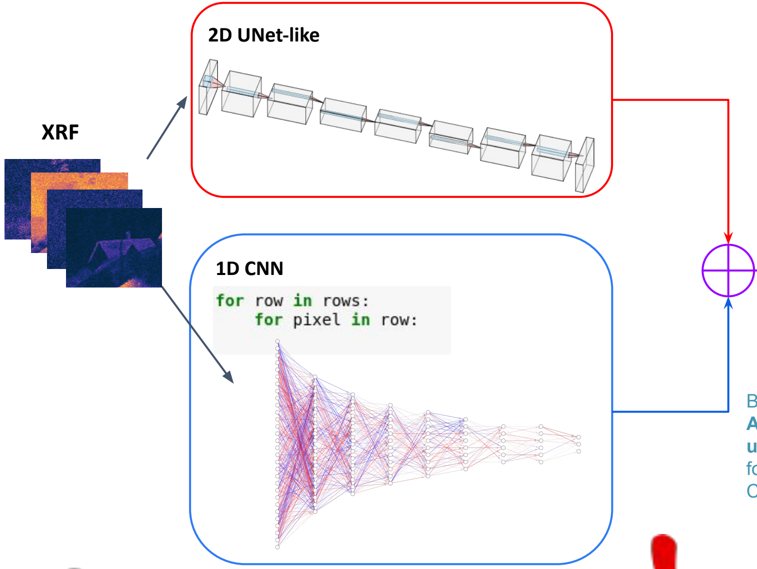
Regione Toscana

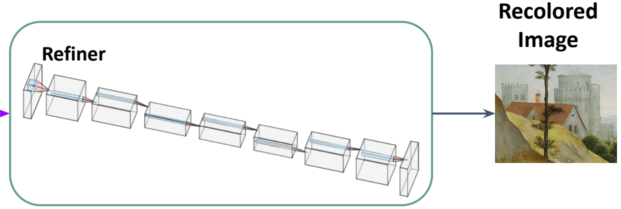
GIOVANISì

AIRES-CH

(*Artificial Intelligence for digital REStoration of Cultural Heritage*)

a.k.a. how to (try to) digitally restore damaged paintings using physics and AI





Bombini, A., Anderlini, L., dell'Agnello, L., Giacomini, F., Ruberto, C., Taccetti, F.: **The AIRES-CH project: Artificial Intelligence for digital REStoration of Cultural Heritages using physical imaging and multidimensional adversarial neural networks**, Accepted for publication on the ICIAP2021 conference proceedings, Springer Lecture Notes in Computer Science vol. 13231

...STARTING SOON...

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Cultural Heritage Network

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WHAT IS AIRES-CH?

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Cultural Heritage Network

Artificial Intelligence for digital REStoration of Cultural Heritage (AIRES-CH) aims at building a web-based app for the digital restoration of pictorial artworks through Computer Vision technologies applied to physical imaging raw data.

The goal is to develop a DNN capable of inferring the RGB image from an XRF image (i.e. the 3D tensor [h,w,E]); this will be obtained by a multi-dimensional DNN, capable of exploiting features of 1D and 2D DNN.

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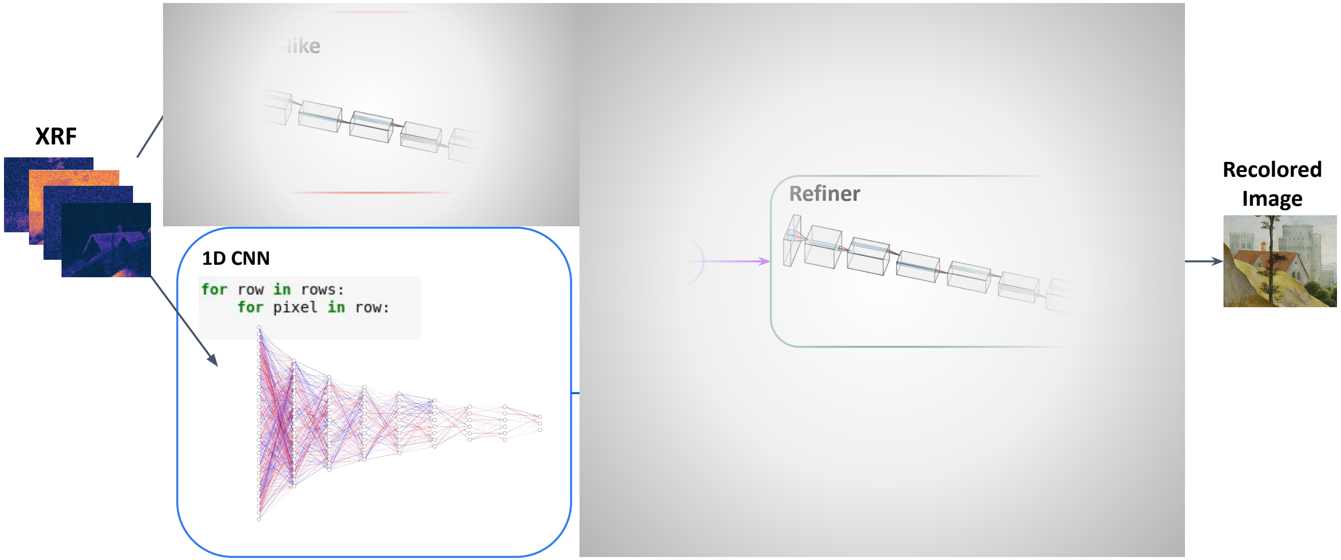

- Learns from **millions** of pixels' histograms
- Learns how to associate RGB to peaks distributions
- Loses spatial correlations

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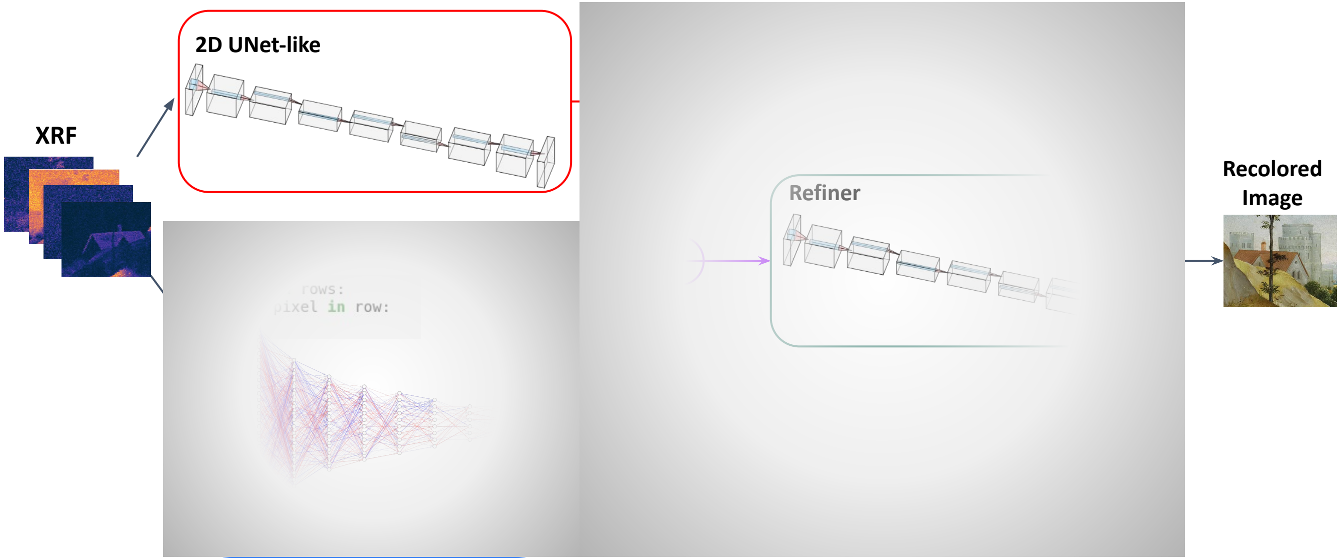

- Learns from **few images**
- Learns how to associate RGB to regions AND peak distributions
- Learns spatial correlations

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WHAT IS AIRES-CH?

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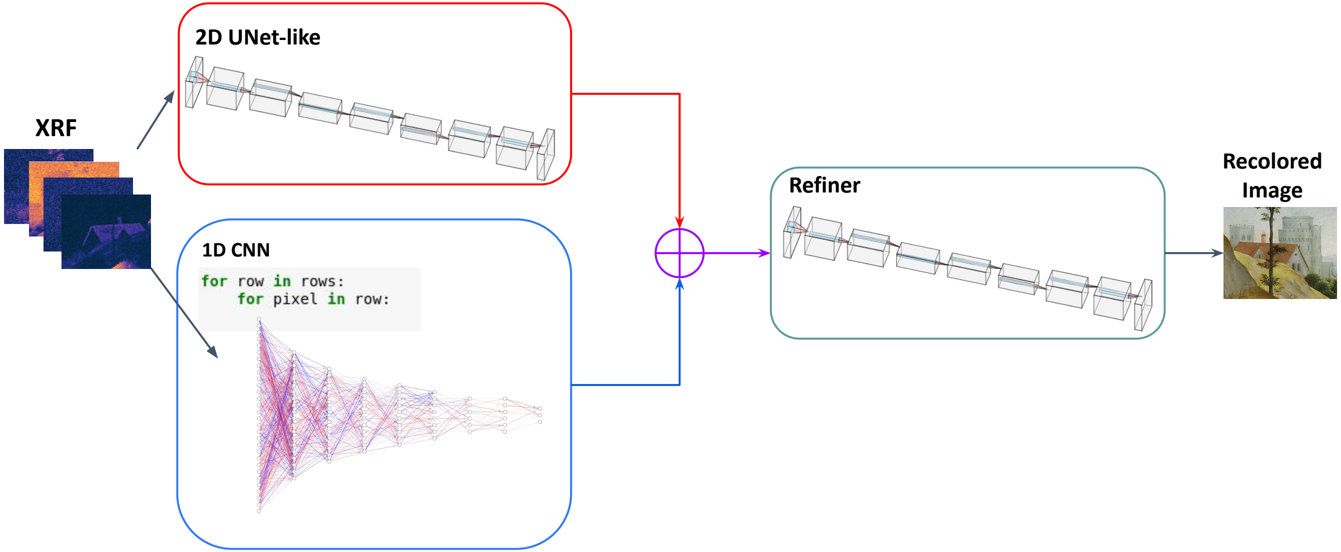

- Learns from **few images** but millions of pixels' histograms
- Learns how to associate RGB to regions AND peak distributions
- Learns spatial correlations
- The refiner networks learns how to properly merge the two

WHY AIRES-CH?

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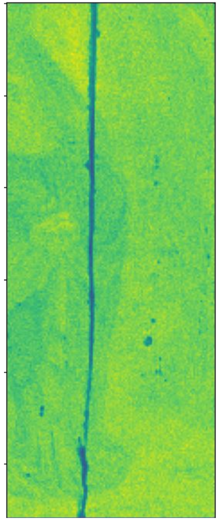

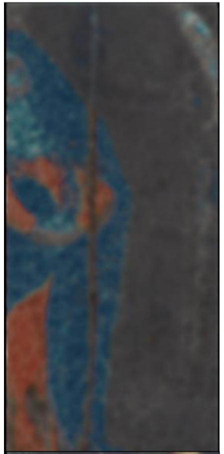

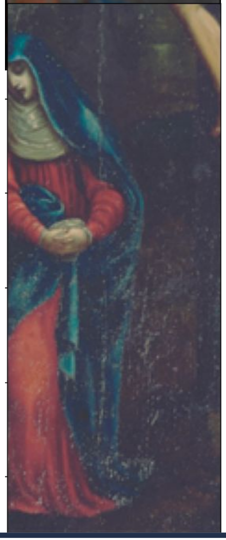

- Sometimes we face multi-layered pictorial artworks with hidden, older, no more visible layers, due to corrections, or pentimenti, or (more) modern restoration processes;
- We may face damaged surfaces, especially of frescoes, where pigments are no more visible but still detectable using nuclear techniques.
- A well-trained Deep Neural Network (DNN), capable of infer RGB from nuclear imaging raw data, may communicate something interesting about the pigment composition upon failing.
  a. Or, even, upon success.

It may be *Lapis Lazuli Blue*; probably it sees **Ca** in the *Lazurite* [$(Na,Ca)_8(AlSiO_4)_6(S,SO_4,Cl)_{1-2}$] and **K**, sometimes substituting the Na. [https://www.mindat.org/min-2357.html]

Crocifissione di Viterbo, Unknown author, XVI sec. circa;
courtesy of Museum Polo Monumentale colle del Duomo, Viterbo & Archeoares srl.

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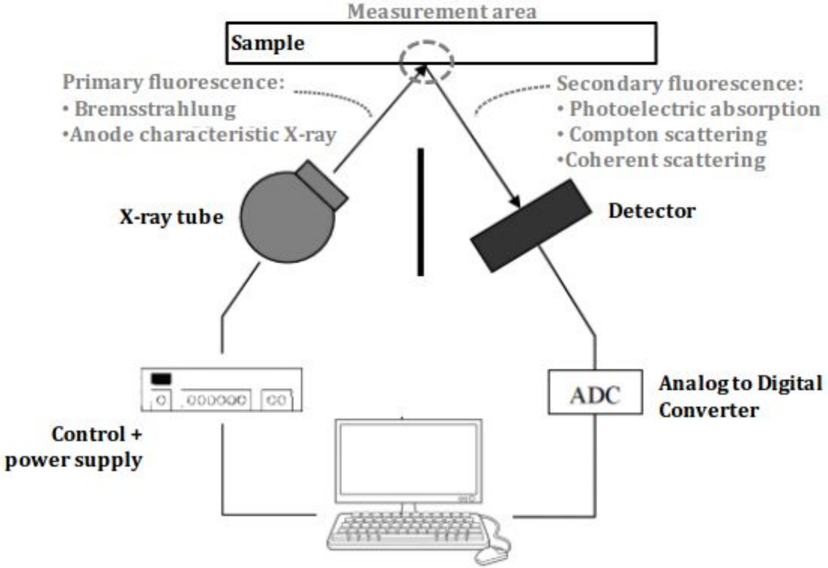
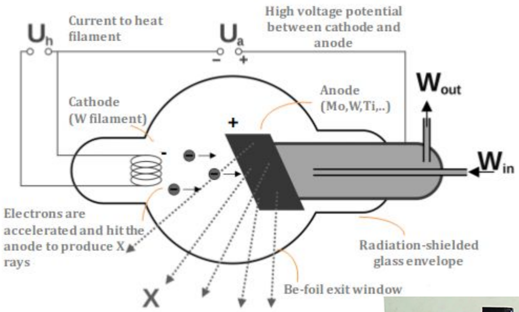
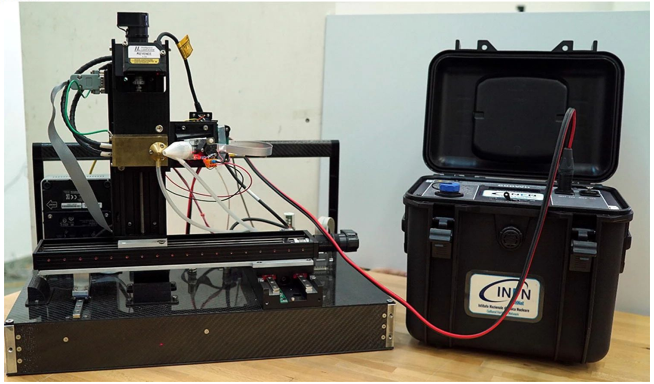
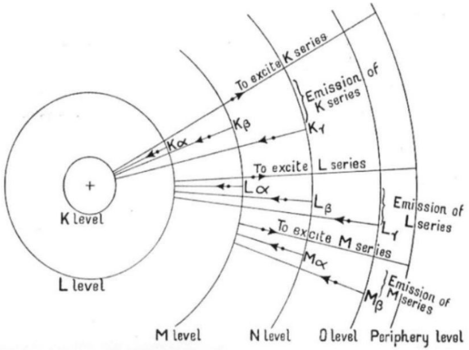
WHAT IS X-RAY FLUORESCENCE?





Portable XRF





Siegbahn	IUPAC	Siegbahn	IUPAC	Siegbahn	IUPAC	Siegbahn	IUPAC
$K\alpha_1$	$K\text{-}L_3$	$L\alpha_1$	$L_3\text{-}M_5$	$L\gamma_1$	$L_2\text{-}N_4$	$M\alpha_1$	$M_5\text{-}N_7$
$K\alpha_2$	$K\text{-}L_2$	$L\alpha_2$	$L_3\text{-}M_4$	$L\gamma_2$	$L_1\text{-}N_2$	$M\alpha_2$	$M_5\text{-}N_6$
$K\beta_1$	$K\text{-}M_3$	$L\beta_1$	$L_2\text{-}M_4$	$L\gamma_3$	$L_1\text{-}N_3$	$M\beta$	$M_4\text{-}N_6$
$K^{I}\beta_2$	$K\text{-}N_3$	$L\beta_2$	$L_3\text{-}N_5$	$L\gamma_4$	$L_1\text{-}O_3$	$M\gamma$	$M_3\text{-}N_5$
$K^{II}\beta_2$	$K\text{-}N_2$	$L\beta_3$	$L_1\text{-}M_3$	$L\gamma_4'$	$L_1\text{-}O_2$	$M\zeta$	$M_{4,5}\text{-}N_{2,3}$
$K\beta_3$	$K\text{-}M_2$	$L\beta_4$	$L_1\text{-}M_2$	$L\gamma_5$	$L_2\text{-}N_1$		
$K^{I}\beta_4$	$K\text{-}N_5$	$L\beta_5$	$L_3\text{-}O_{4,5}$	$L\gamma_6$	$L_2\text{-}O_4$		
$K^{II}\beta_4$	$K\text{-}N_4$	$L\beta_6$	$L_3\text{-}N_1$	$L\gamma_8$	$L_2\text{-}O_1$		
$K\beta_{4x}$	$K\text{-}N_4$	$L\beta_7$	$L_3\text{-}O_1$	$L\gamma_8'$	$L_2\text{-}N_{6(7)}$		
$K^{I}\beta_5$	$K\text{-}M_5$	$L\beta_7'$	$L_3\text{-}N_{6,7}$	$L\eta$	$L_2\text{-}M_1$		
$K^{II}\beta_5$	$K\text{-}M_4$	$L\beta_9$	$L_1\text{-}M_5$	Ll	$L_3\text{-}M_1$		
		$L\beta_{10}$	$L_1\text{-}M_4$	Ls	$L_3\text{-}M_3$		
		$L\beta_{15}$	$L_3\text{-}N_4$	Lt	$L_3\text{-}M_2$		
		$L\beta_{17}$	$L_2\text{-}M_3$	Lu	$L_3\text{-}N_{6,7}$		
				Lv	$L_2\text{-}N_{6(7)}$		

Taccetti, F., Castelli, L., Czelusniak, C. et al. **A multipurpose X-ray fluorescence scanner developed for in situ analysis**. *Rend. Fis. Acc. Lincei 30, 307–322* (2019). https://doi.org/10.1007/s12210-018-0756-x

WHAT IS X-RAY FLUORESCENCE?

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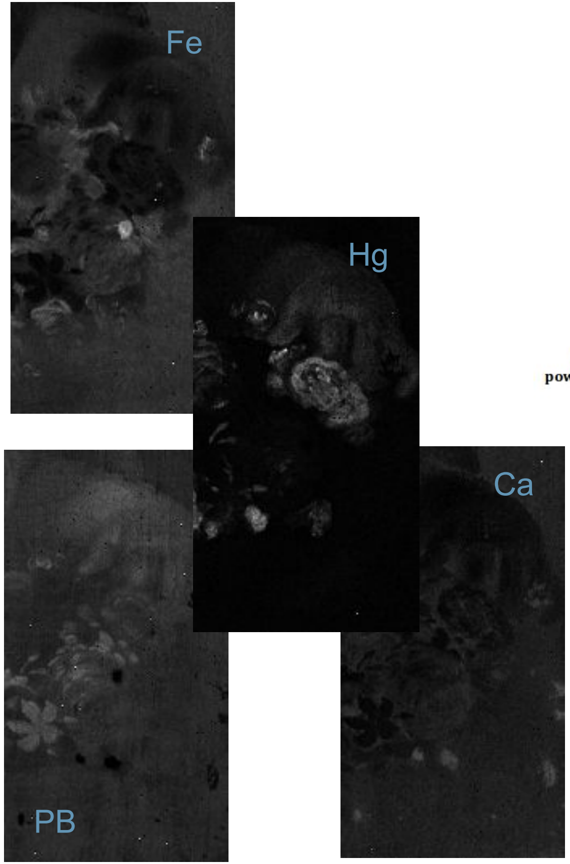
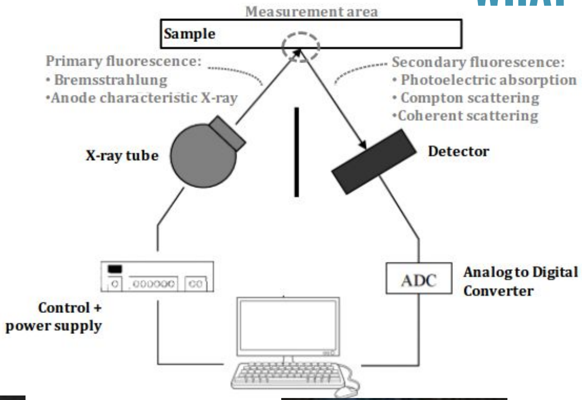
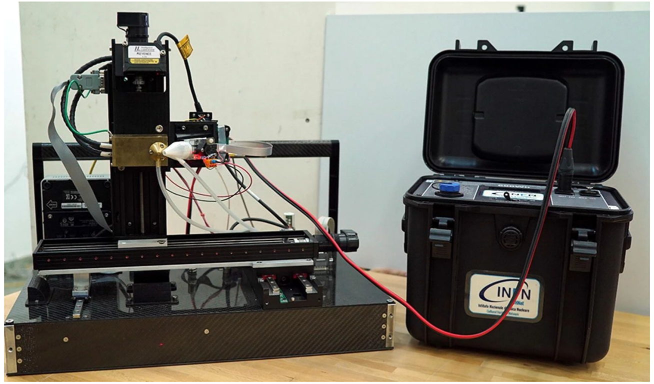




Portable XRF

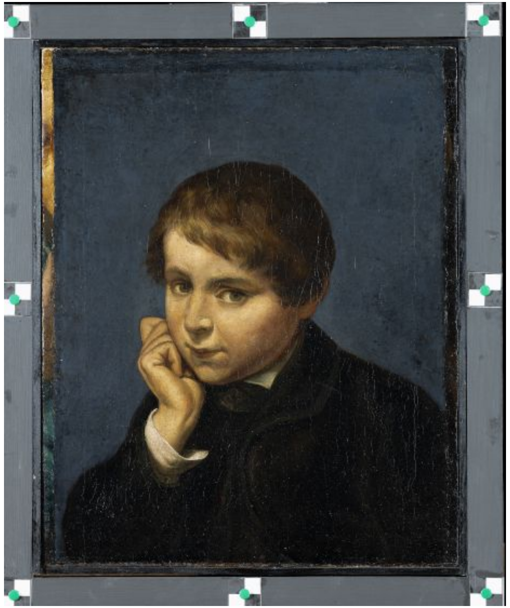


[XRF visualiser]

Taccetti, F., Castelli, L., Czelusniak, C. et al. **A multipurpose X-ray fluorescence scanner developed for in situ analysis**. *Rend. Fis. Acc. Lincei 30, 307–322* (2019). https://doi.org/10.1007/s12210-018-0756-x

WHY X-RAY FLUORESCENCE?

- It provides fast, sensitive, multi-elemental **non-invasive, non-destructive analysis**. It is perfect for Cultural Heritage applications;
- It can be performed with portable apparatus for *in-situ* analysis (e.g. in museums).
- Can produce macro-maps [~ O(meter)]
- It is able to detect signal coming **from hidden pictorial layers,** underneath the outermost one.
- IT IS AVAILABLE TO US.



➢ **Visible Layer**, Ragazzo Triste, XVIII sec. Circa, *Unknown author*

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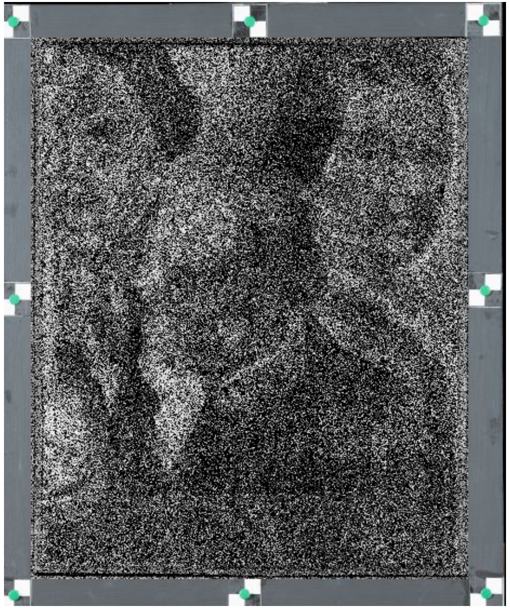

XRF Sb image, Ragazzo Triste, XVIII sec. Circa, *Unknown author* ➢

AIRES-CH
Training Dataset

TRAINING DATASET

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The whole dataset is composed by 62 XRF raw data coming from several XRF analysis on multiple paintings performed both in the LABEC facility in Florence, as well as in situ analysis (*the data comes not only from published works, and include some private artworks*).

For training the 1D models, only a 50% of the pixels where used (being randomly chosen), giving a training dataset of around 2,059,780 [histogram, RGB] pairs, divided into training, test, and validation set.

For training the 2D models, 45 XRF scans are used, reserving the remaining as 9 for test, and 8 for validation.

The raw data are obtained by three different devices, all developed, built and assembled by CHNet.

The raw data comes from different artwork typologies: multi-layered paintings, drawings without preparatory layers, and illuminated manuscripts, all over different periods and epochs (from middle ages to contemporary art).

It is worth noticing that artworks from different epochs might have been realised using different pigments. Visually similar colour can therefore be associated to completely different XRF spectra depending on the painting's epoch.

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AIRES-CH

Neural Network Architectures

1D Branch

1D BRANCH MODELS

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- **We have developed and trained few DNN models:**
  1. Dense
  2. CNN
  3. ResNet-like
  4. Inception-like
  5. Custom Model
  6. FractalNet
  7. (Dilated)WaveNet
- **All of them were (moderately) capable of inferring the RGB from the XRF histogram.**
  - ➢ Three of them were slightly more performing

1D BRANCH MODELS

- We have developed and trained few DNN models:
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1D BRANCH MODELS

more on v7

- We have developed and trained few DNN models:
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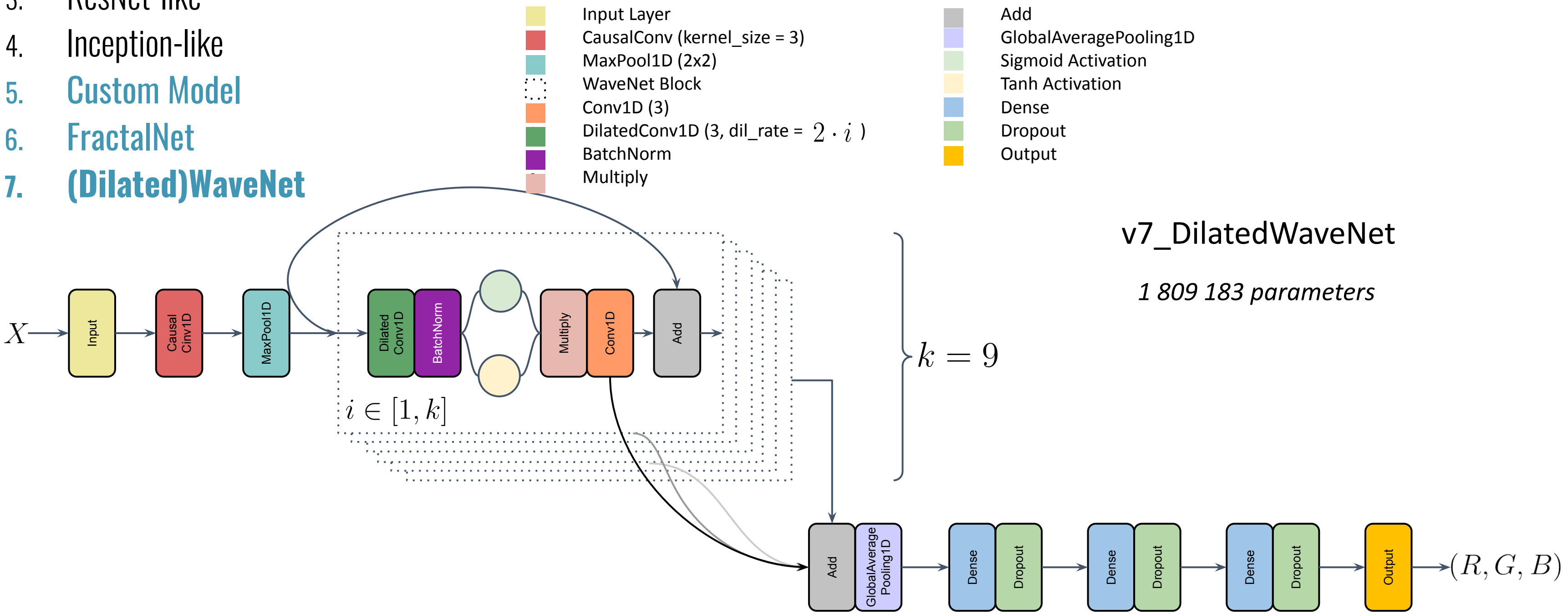
  3. ResNet-like
  4. Inception-like
  5. Custom Model
  6. FractalNet
  7. **(Dilated)WaveNet**



v7_DilatedWaveNet

1 809 183 parameters

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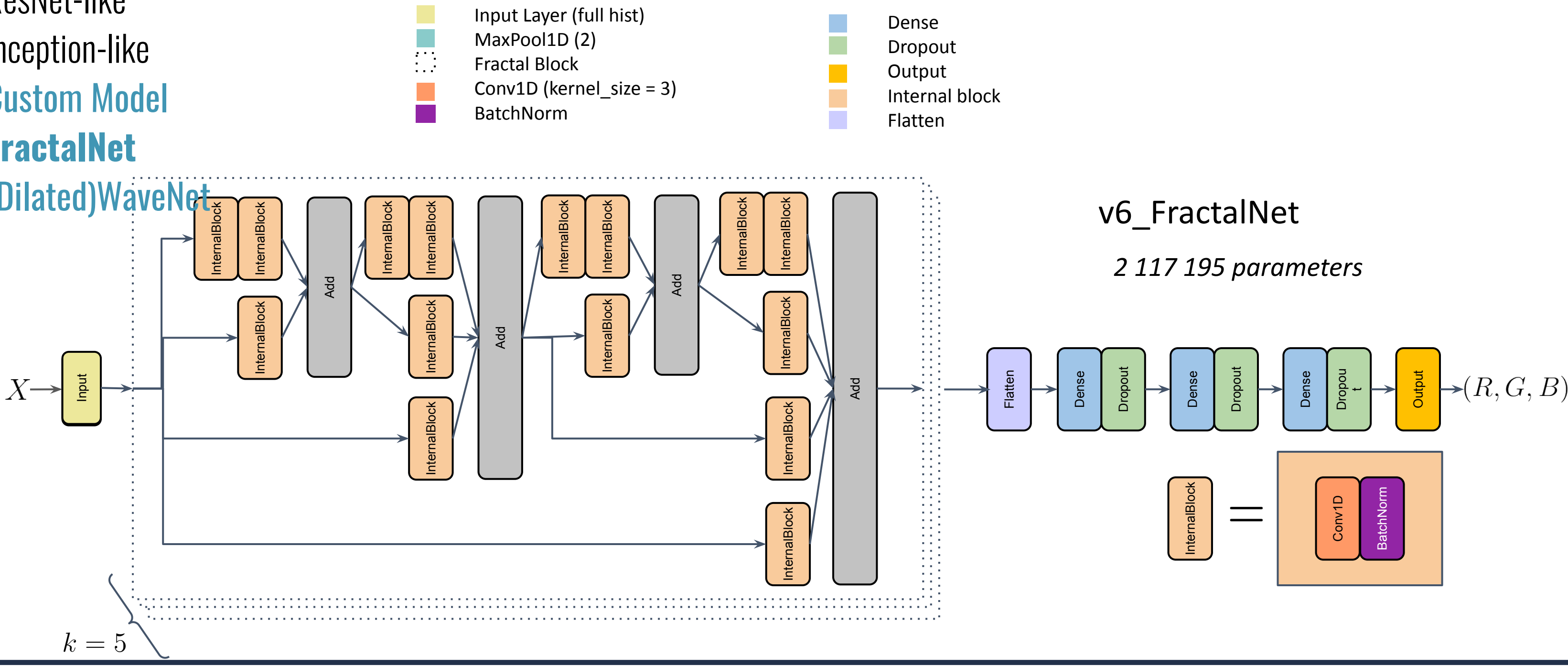
1D BRANCH MODELS

more on v6

- We have developed and trained few DNN models:
  1. Dense
  2. CNN
  3. ResNet-like
  4. Inception-like
  5. Custom Model
  6. **FractalNet**
  7. (Dilated)WaveNet



v6_FractalNet

2 117 195 parameters

1D BRANCH MODELS

more on v5

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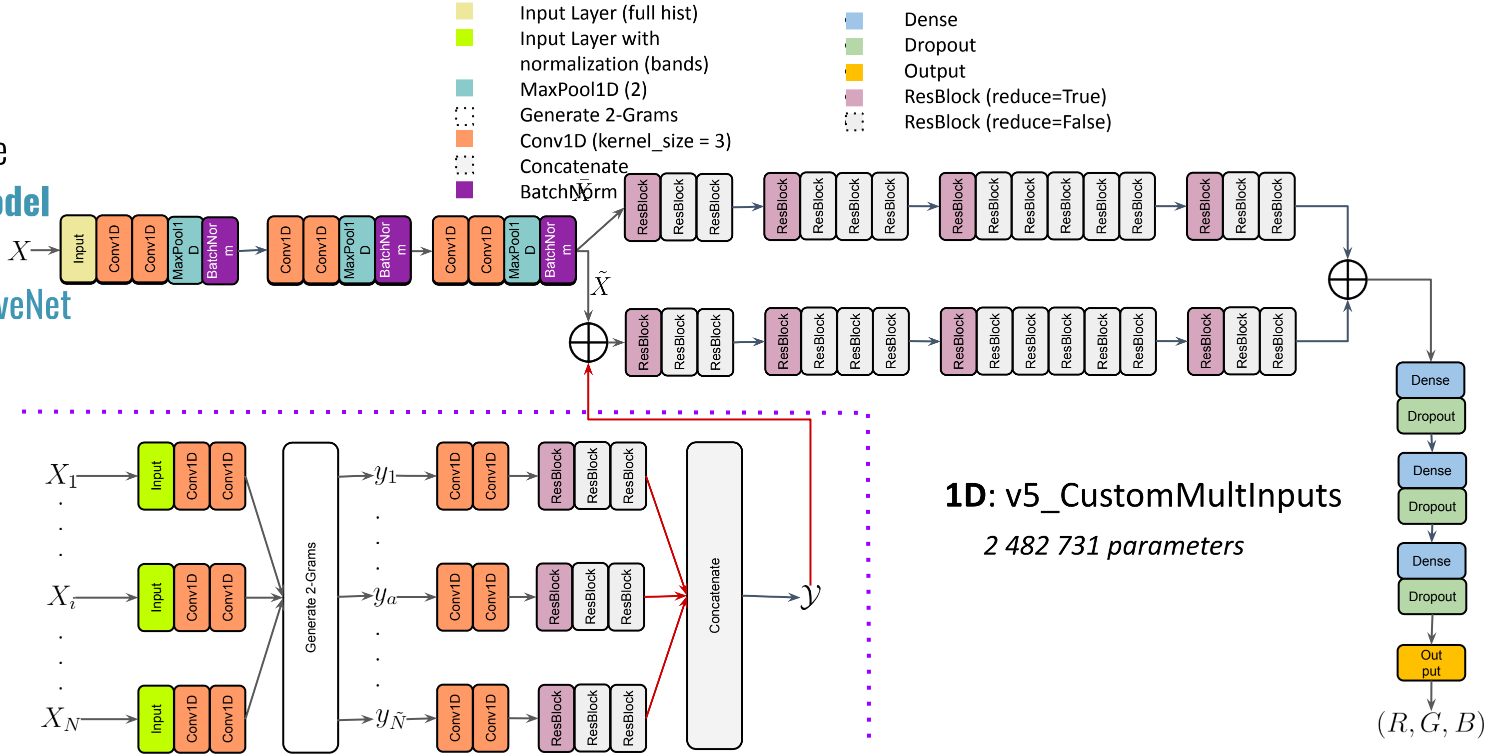

Tin (Sn) Kα
Potassium (K) Kα
Manganese (Mn) Kα
Titanium (Ti) Kα

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1D BRANCH MODELS

more on scores

- We have developed and trained few DNN models:
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  7. (Dilated)WaveNet

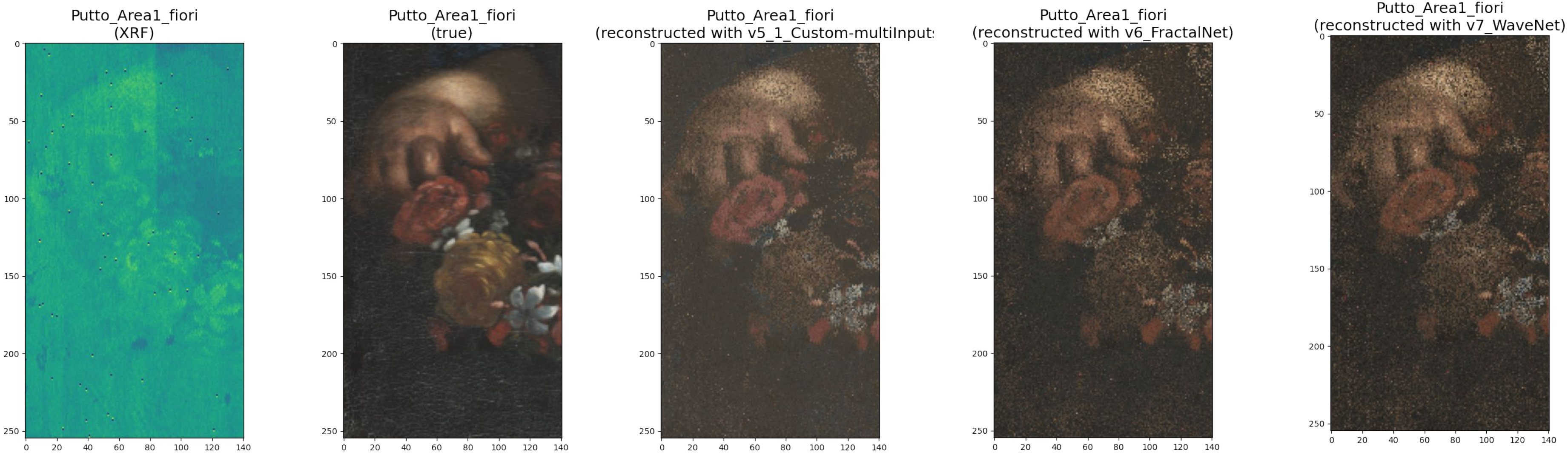
	SSIM	MS-SSIM	PSNR
v5_CustomMultInputs	$\boxed{0.388}$	$\boxed{0.680}$	$\boxed{20.104}$
v6_FractalNet	0.372	0.677	20.076
v7_WaveNet	0.356	0.673	19.980

- All of them were (moderately) capable of inferring the RGB from the XRF histogram.
  - Three of them were slightly more performing
- We checked the performances using:
  - Structural Similarity Index Measure (SSIM)
  - Multi-Scale SSIM (MS-SSIM)
  - Peak Signal-to-Noise Ratio (PSNR)

	Binary Cross-Entropy	Mean Squared Error
v5_CustomMultInputs	0.636	$\boxed{0.0138}$
v6_FractalNet	0.633	0.0141
v7_WaveNet	$\boxed{0.629}$	0.0146

EXAMPLE ON VALIDATION RAW DATA - *multilayered painting*

GOOD



Model parameters: 2482731
Losses: SSIM=0.497; MS-SSIM=0.84; PSNR=22.048; BCE=0.6; MSE=0.006;

Model parameters: 2117195
Losses: SSIM=0.437; MS-SSIM=0.823; PSNR=23.253; BCE=0.543; MSE=0.005;

Model parameters: 1809183
Losses: SSIM=0.397; MS-SSIM=0.816; PSNR=23.101; BCE=0.532; MSE=0.005;

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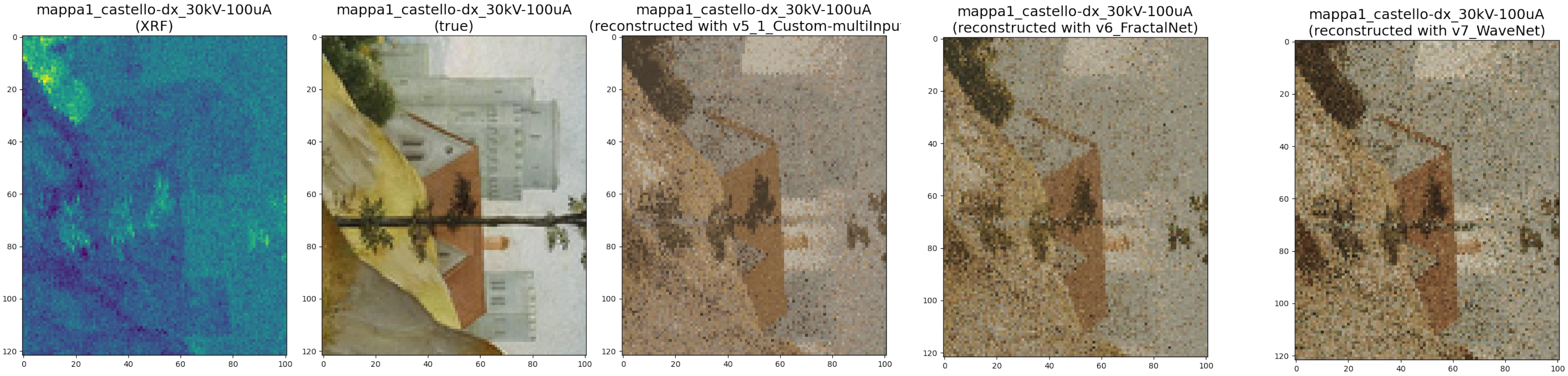
EXAMPLE ON VALIDATION RAW DATA - *multilayered painting*

GOOD



Model parameters: 2482731
Losses: SSIM=0.35; MS-SSIM=0.744; PSNR=17.124; BCE=0.71; MSE=0.019;

Model parameters: 2117195
Losses: SSIM=0.321; MS-SSIM=0.732; PSNR=16.942; BCE=0.705; MSE=0.02;

Model parameters: 1809183
Losses: SSIM=0.277; MS-SSIM=0.734; PSNR=16.389; BCE=0.701; MSE=0.023;

EXAMPLE ON VALIDATION RAW DATA - *illuminated manuscripts*

NOT GOOD

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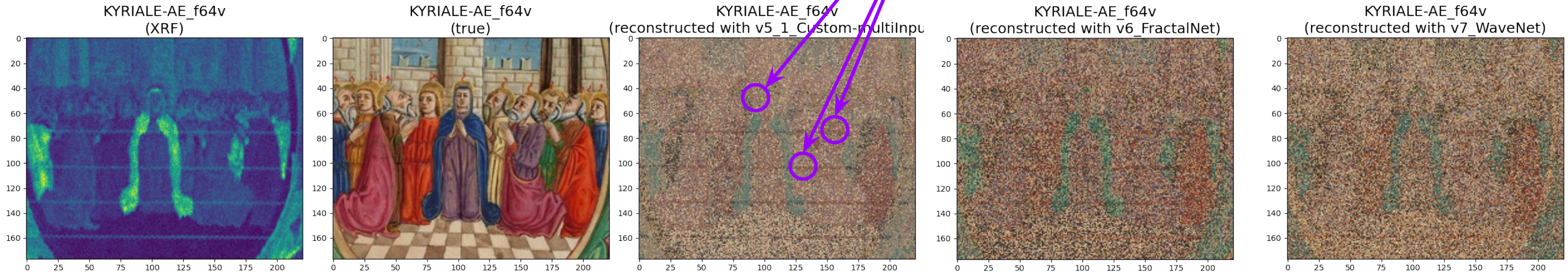
Pentagram drawn in the back page;
XRF sees behind outermost pictorial layer

too many layers are difficult to recolor



Model parameters: 2482731
Losses: SSIM=0.058; MS-SSIM=0.209; PSNR=13.816; BCE=0.767; MSE=0.042;

Model parameters: 2117195
Losses: SSIM=0.041; MS-SSIM=0.202; PSNR=13.469; BCE=0.744; MSE=0.045;

Model parameters: 1809183
Losses: SSIM=0.041; MS-SSIM=0.21; PSNR=13.308; BCE=0.748; MSE=0.047;

AIRES-CH

Neural Network Architectures

2D Branch

2D BRANCH MODELS

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Cultural Heritage Network

- Due to the higher computational costs, we have developed and trained 2 DNN UNet-like models:
  1. VGG-like
  2. DilResNet-like

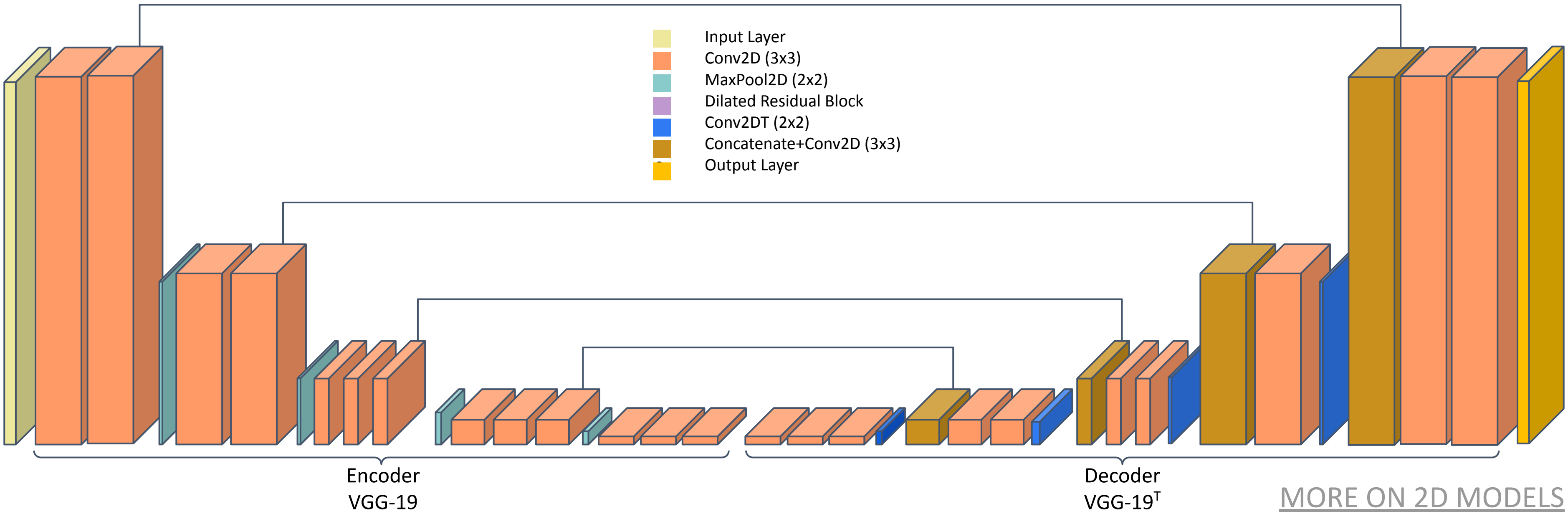
2D BRANCH MODELS

INFN CHNet
Istituto Nazionale di Fisica Nucleare
Cultural Heritage Network

- Due to the higher computational costs, we have developed and trained 2 DNN UNet-like models:
  1. **VGG-like**
  2. DilResNet-like

2D: VGG UNet

15 246 659 parameters



MORE ON 2D MODELS

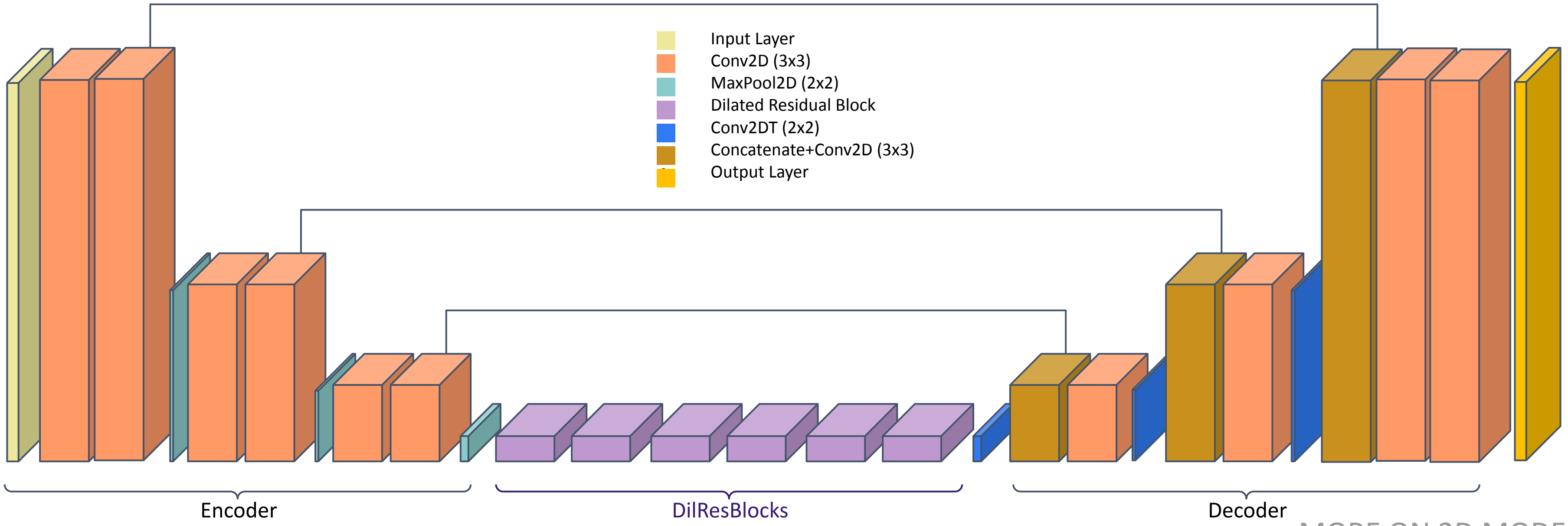
2D BRANCH MODELS

INFN CHNet
Istituto Nazionale di Fisica Nucleare
Cultural Heritage Network

- Due to the higher computational costs, we have developed and trained 2 DNN UNet-like models:
  1. VGG-like
  2. **DilResNet-like**

2D: Dilated Residual UNet

2 179 779 parameters



MORE ON 2D MODELS

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2D BRANCH MODELS

- Due to the higher computational costs, we have developed and trained 2 DNN UNet-like models:
  1. VGG-like
  2. DilResNet-like

- Both were, again, (moderately) capable of inferring the RGB from the XRF histogram.
  - ➢ They seems to outperform 1D models on each score/metric **BUT MS-SSIM**
  - ➢ The best performing model out of the two is the **DilResNet model.**

	SSIM	MS-SSIM	PSNR
VGG	0.733	0.626	19.691
DilResNet	0.745	0.669	21.097

	Binary Cross-Entropy	Mean Squared Error
VGG	0.480	0.0159
DilResNet	0.460	0.0121

EXAMPLE ON VALIDATION RAW DATA - *multilayered painting*

GOOD

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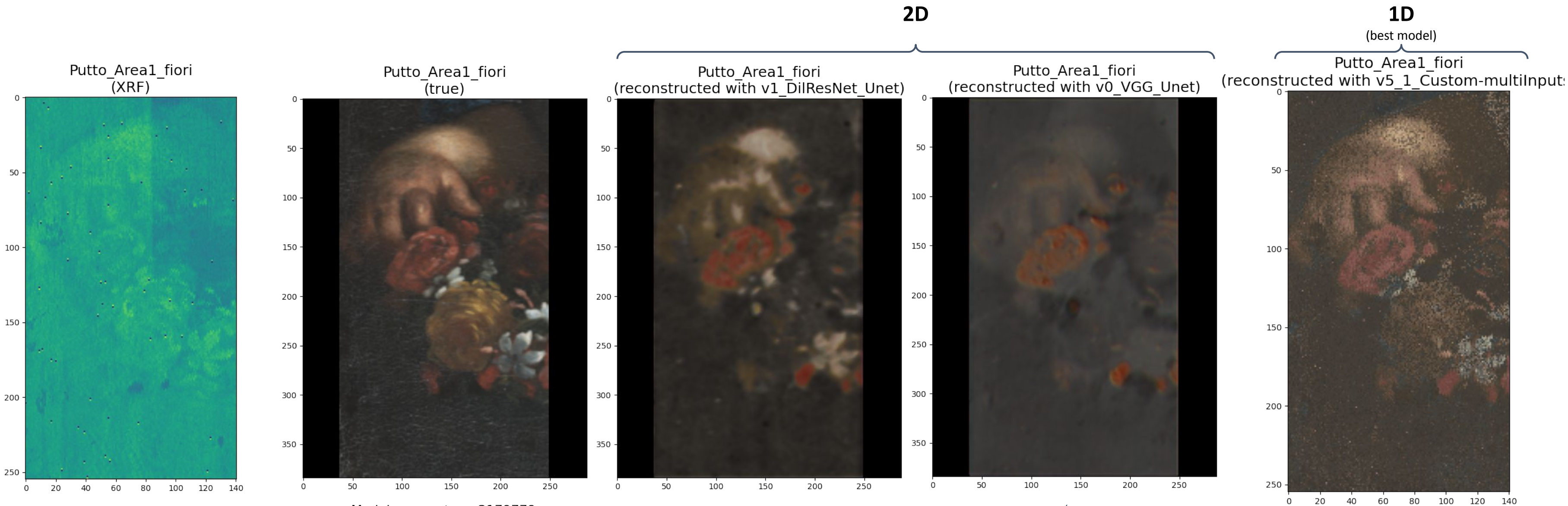

Model parameters: 2179779
Losses: SSIM=0.818; MS-SSIM=0.81; PSNR=25.529; BCE=0.366; MSE=0.002;

Model parameters: 15246659
Losses: SSIM=0.807; MS-SSIM=0.726; PSNR=23.868; BCE=0.407; MSE=0.004;

MS-SSIM best score

Model parameters: 2482731
Losses: SSIM=0.497; MS-SSIM=0.84; PSNR=22.048; BCE=0.6; MSE=0.006;

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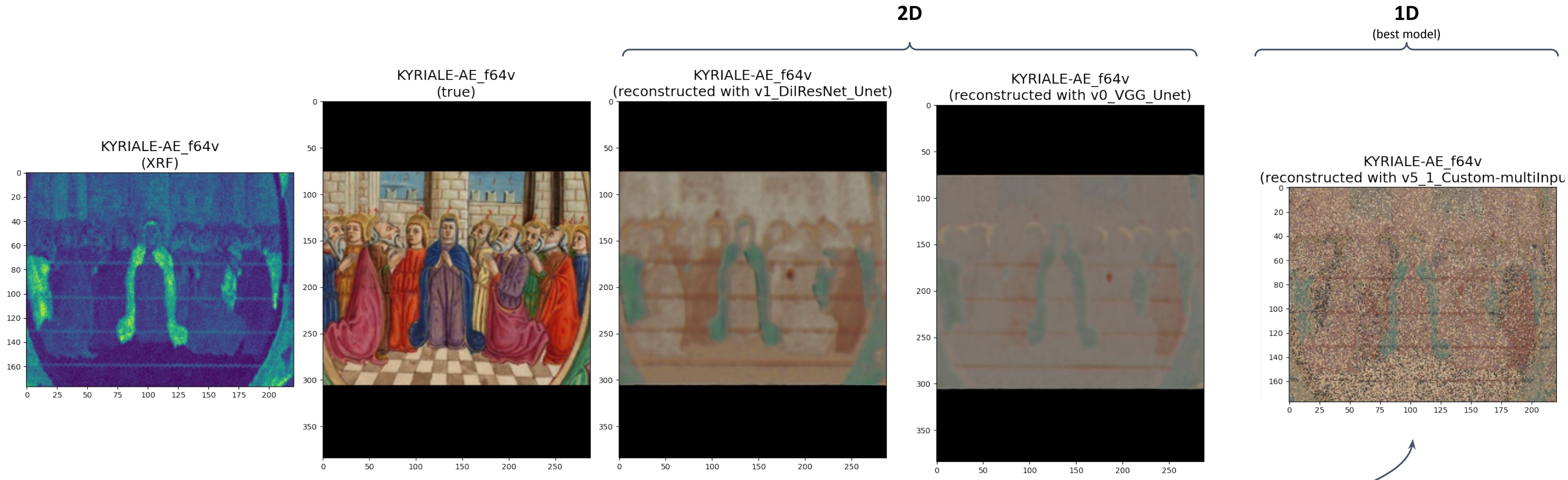
EXAMPLE ON VALIDATION RAW DATA - *illuminated manuscripts*

NOT GOOD



Model parameters: 2179779
Losses: SSIM=0.55; MS-SSIM=0.566; PSNR=18.204; BCE=0.442; MSE=0.015;

Model parameters: 15246659
Losses: SSIM=0.546; MS-SSIM=0.505; PSNR=17.381; BCE=0.465; MSE=0.018;

Model parameters: 2482731
Losses: SSIM=0.058; MS-SSIM=0.209; PSNR=13.816; BCE=0.767; MSE=0.042;

Here 2D outperforms 1D

AIRES-CH
Conclusions
Outlook

CONCLUSIONS & OUTLOOK

- We have shown that the goal of inferring an RGB image from an XRF raw data is feasible.
  - We have developed both 1D & 2D branches
- We have planned a new measurement campaign, jointly with Biblioteca Marucelliana, Firenze, on their drawings, to enlarge and standardise the training dataset.
- We have started using *Optuna* to perform hyperparameter optimisation of the models.
- We have embedded an alpha version on the network inside our XRF web tool
- We are going to develop the technique to take into account the presence of hidden pictorial layers and to recolour them, somehow factoring out the contribution from the outermost layer.
- This is not the only application: we can use Internet Of Things (IoT) and link to the web the imaging instruments *(especially the portable ones for in situ analysis, like XRF and MACHINA)*, so that we can send to server the raw data to have *real-time recoloring.*

Bombini, A., Anderlini, L., dell'Agnello, L., Giacomini, F., Ruberto, C., Taccetti, F.: **Hyperparameter optimisation of Artificial Intelligence for digital REStoration of Cultural Heritages (AIRES-CH) models**, Under review Workshop on Advancements in Applied Machine-learning and Data Analytics (AAMDA), Springer Lecture Notes in Computer Science

Thank you for your attention!

Alessandro Bombini
email: bombini@fi.infn.it

COMPETENCE CENTRE FOR THE CONSERVATION OF CULTURAL HERITAGE

Coordination and Harmonisation of National &Thematic Initiatives to support EOSC

Regione Toscana

Extra slides

Alessandro Bombini
email: bombini@fi.infn.it

INFN CHNet

4CH
COMPETENCE CENTRE FOR THE CONSERVATION OF CULTURAL HERITAGE

EOSC-Pillar
Coordination and Harmonisation of National &Thematic Initiatives to support EOSC

Regione Toscana

GIOVANISì

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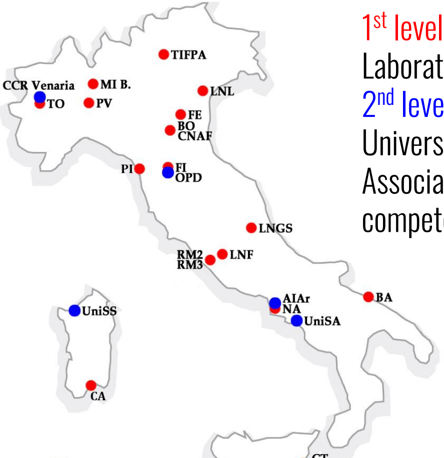
Cultural Heritage Network

INFN-CHNet
Cultural Heritage Network
how it is organised

GO BACK

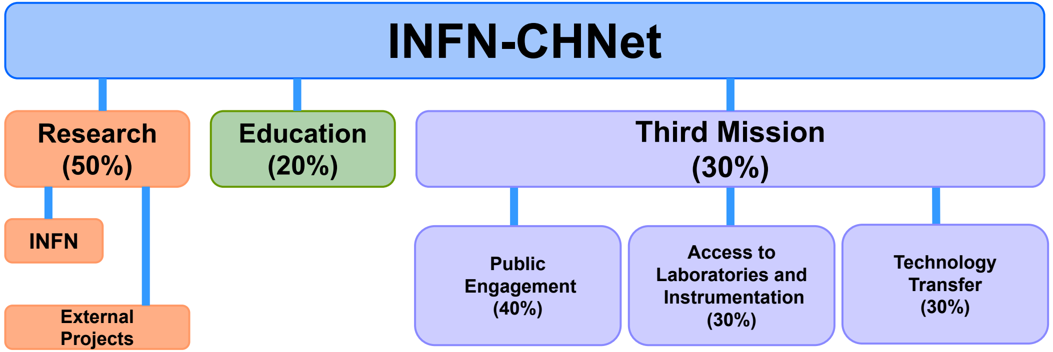


1st level nodes:
Laboratories in INFN facilities
2nd level nodes:
Universities, Restoration Centres, Associations, with complementary competencies

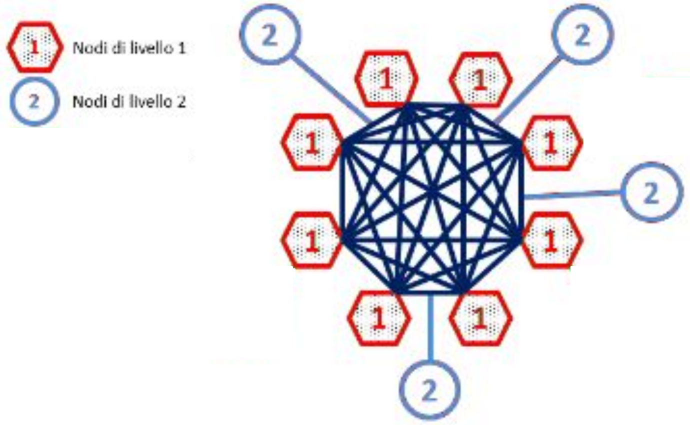
GO BACK

The INFN
Cultural Heritage Network

INFN CHNet
Istituto Nazionale di Fisica Nucleare
Cultural Heritage Network



3rd level nodes:
Foreign research centres/Universities outside Europe.
- Each 3rd level node is bound to a 1st level node
- Each 3rd level node is encouraged to create a local network with different competencies in its own country



Giuntini, L.; Castelli, L.; Massi, M.; Fedi, M.; Czelusniak, C.; Gelli, N.; Liccioli, L.; Giambi, F.; Ruberto, C.; Mazzinghi, A.; Barone, S.; Marchegiani, F.; Nisi, S.; Lubritto, C.; Altieri, S.; Tortora, L.; Branchini, P.; Fabbri, A.; Graziani, V.; Lins, S.B.; Guidorzi, L.; Lo Giudice, A.; Re, A.; Sottili, L.; Balerna, A.; Cestelli Guidi, M.; Pronti, L.; Romani, M.; Albertin, F.; Bettuzzi, M.; Brancaccio, R.; Morigi, M.P.; Alloni, D.; Salvini, A.; Smilgys, B.; Prata, M.; Altieri, S.; Bonesini, M.; Di Martino, D.; Clemenza, M.; Carpinelli, M.; Oliva, P.; Sipala, V.; Gueli, A.M.; Pasquale, S.; Stella, G.; Pepponi, G.; Grazzi, F.; Taccetti, F. Detectors and Cultural Heritage: **The INFN-CHNet Experience**. *Appl. Sci.* **2021**, *11*, 3462. https://doi.org/10.3390/app11083462

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The INFN-CHNET
Digital Heritage Laboratory

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INFN-CHNet is organised in three research domain:

1. FixLab: the ensemble of immovable apparatus for in-lab analysis
2. MoLab: the ensemble of movable apparatus for in-situ analysis
3. DHLab: the ensemble of digital services for research.

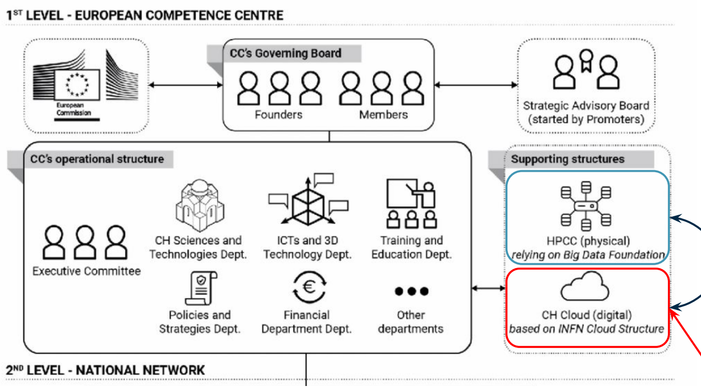
The DHLab (*Digital Heritage Laboratory*) is in charge of developing software service for the INFN-CHNet researchers, (mostly of which) to be offered on the CHNet cloud, mainly in the EU Projects Ariadne+, EOSC-Pillar and 4CH.

It currently offers cloud services developed within 2 european projects, EOSC-Pillar and Ariadne+. In the near future, they will be integrated into the 4CH competence center on Cultural Heritage, where INFN is task leader of the Tasks 3.3 *(Cultural Heritage Cloud)* and 3.5 *(Big Data Services)*.

ARIADNE plus

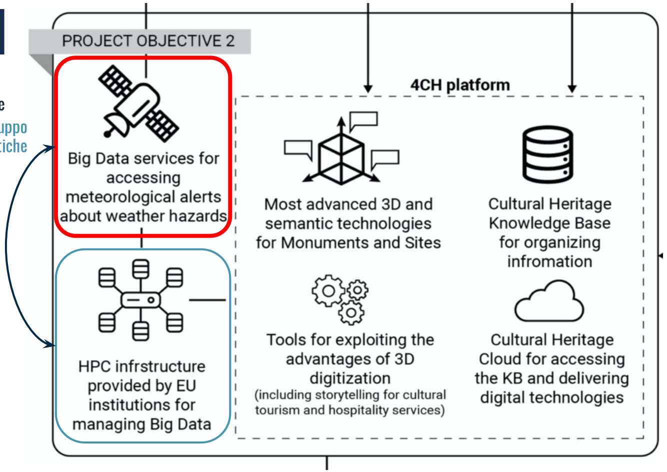
EOSC-Pillar
Coordination and Harmonisation of National &Thematic Initiatives to support EOSC

Bombini, A., Castelli, L., dell'Agnello, L., Felicetti, A., Giacomini, F., Niccolucci, F., Taccetti, F.: **CHNet cloud: an EOSC-based cloud for physical technologies applied to cultural heritages**. In: *GARR (ed.) Conferenza GARR 2021 - Sostenibile/Digitale. Dati e tecnologie per il futuro.* (2021). https://doi.org/10.26314/GARR-Conf21-proceedings-09,



INFN CNAF
Istituto Nazionale di Fisica Nucleare
Centro Nazionale per la Ricerca e lo Sviluppo nelle Tecnologie Informatiche e Telematiche

INFN CHNet
CHNet cloud



4CH

It is also involved in digital technology research.

The INFN-CHNet Florence node

LABEC

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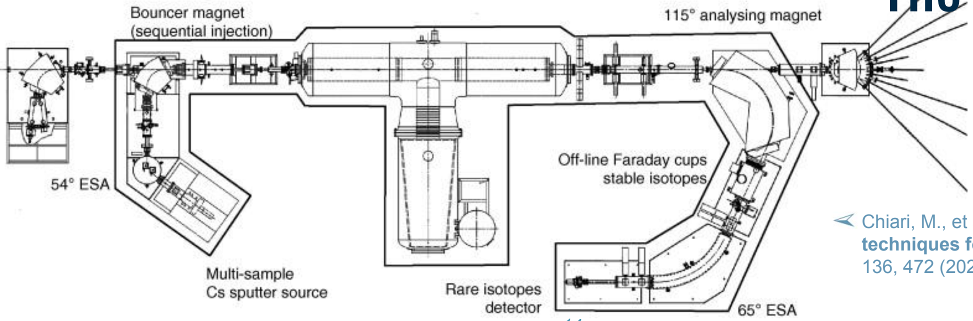
3MV Tandetron



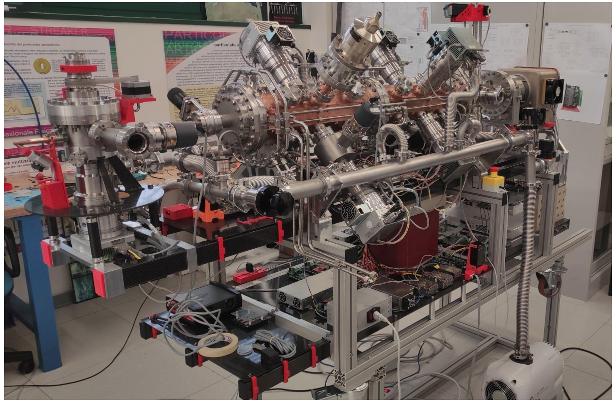
PIXE-PIGE line

^{14}*C AMS line*

Chiari, M., et al. **LABEC, the INFN ion beam laboratory of nuclear techniques for environment and cultural heritage.** Eur. Phys. J. Plus 136, 472 (2021). https://doi.org/10.1140/epjp/s13360-021-01411-1

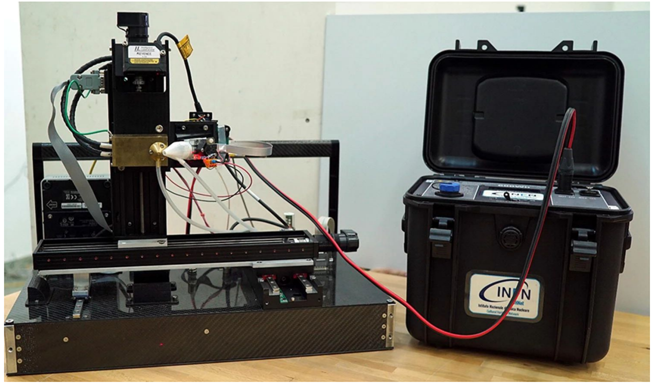
MACHINA

(Movable Accelerator for Cultural Heritage In-situ Non-destructive Analysis)



S. Mathot, G. Anelli, S. Atieh, A. Bilton, B. Bulat, Th. Callamand, S. Calvo, G. Favre, J.-M. Geisser, A. Gerardin, A. Grudiev, A. Lombardi, E. Montesinos, F. Motschmann, H. Pommerenke, P. Richerot, K. Scibor, M. Timmins, M. Vretenar, F. Taccetti, F. Benetti, L. Castelli, M. Chiari, C. Czelusniak, S. Falciano, M. Fedi, P.A. Mandò, M. Manetti, C. Matacotta, E. Previtali, C. Ruberto, V. Virgili, L. Giuntini, **The CERN PIXE-RFQ, a transportable proton accelerator for the machina project**, *Nuclear Instruments and Methods in Physics Research Section B*, https://doi.org/10.1016/j.nimb.2019.08.025

Portable XRF



Taccetti, F., Castelli, L., Czelusniak, C. et al. **A multipurpose X-ray fluorescence scanner developed for in situ analysis**. *Rend. Fis. Acc. Lincei 30, 307–322* (2019). https://doi.org/10.1007/s12210-018-0756-x

DHLAB tools

XRF visualizer

how it works

GO BACK

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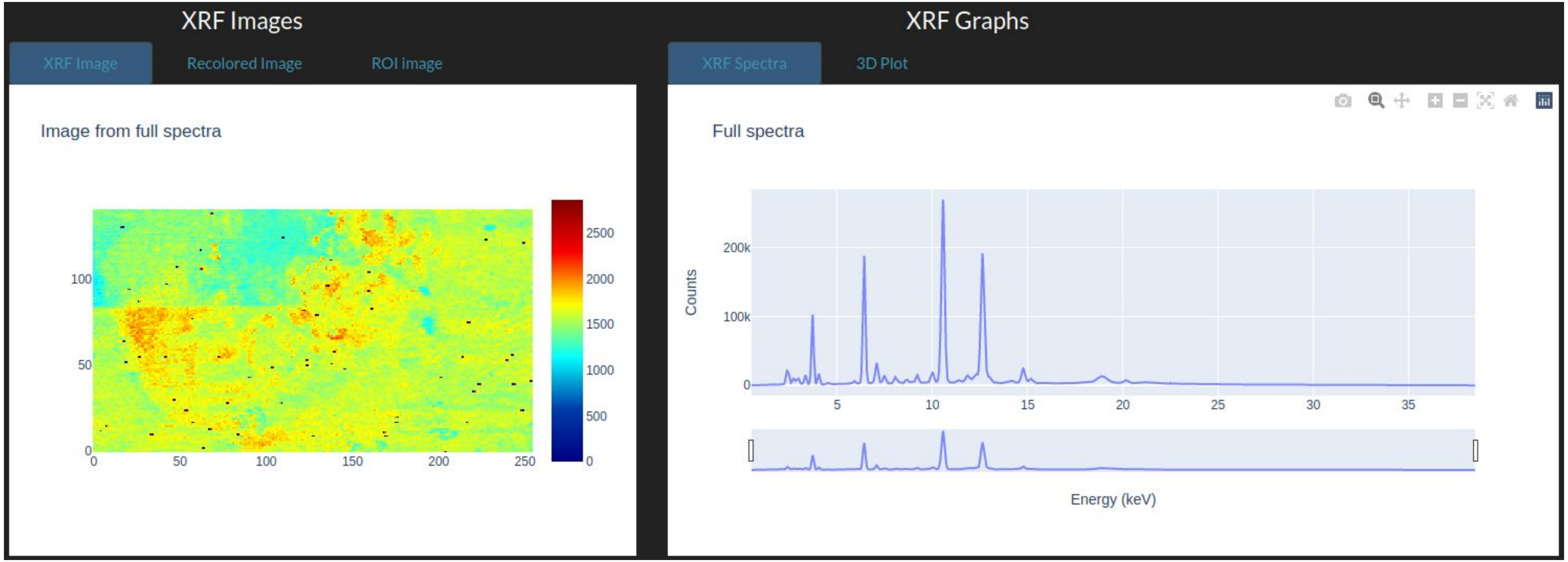

The XRF (X-Ray Fluorescence) is a physical imaging technology, which allows researchers to explore the elemental composition of a study object;

Applied to pictoric image, such a painting or a fresco, or to a document, such miniated manuscripts, allows us to understand the elemental composition of pigments.

The *XRF Analyser* service is designed to allow researchers to perform real-time in-browser elaborations and visualization of XRF raw data.

User may easily visualize the XRF image with few clicks.

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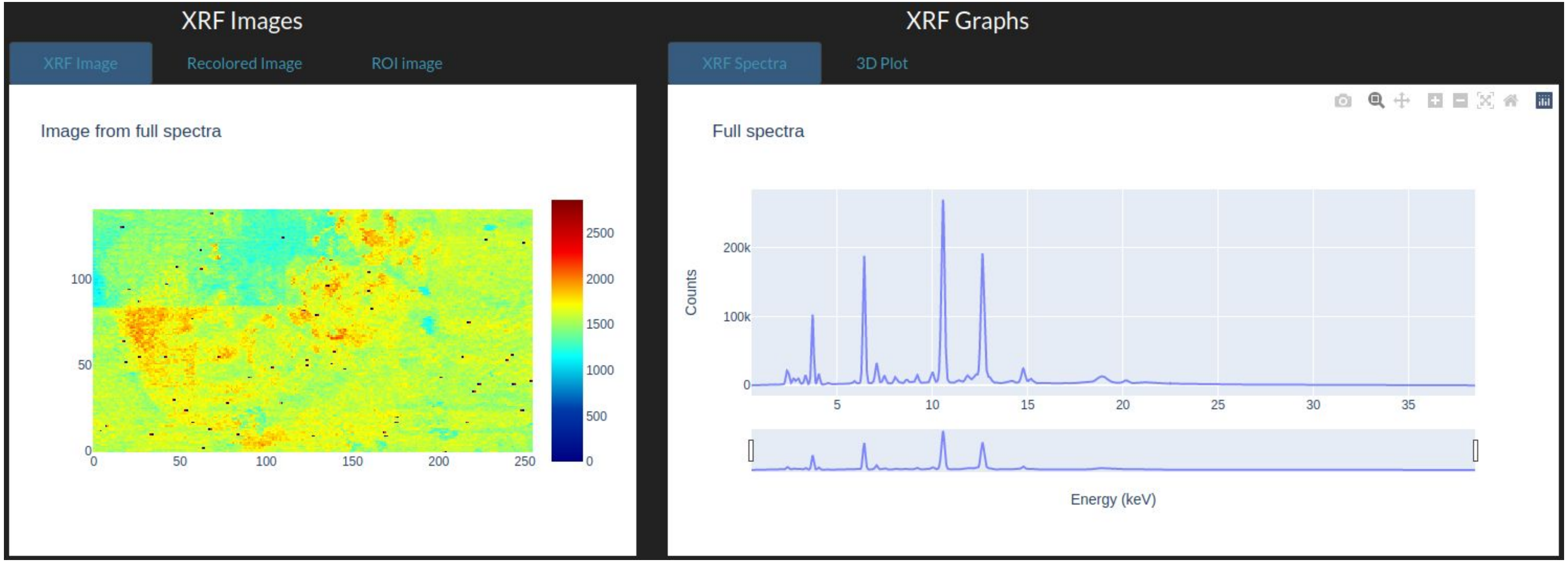

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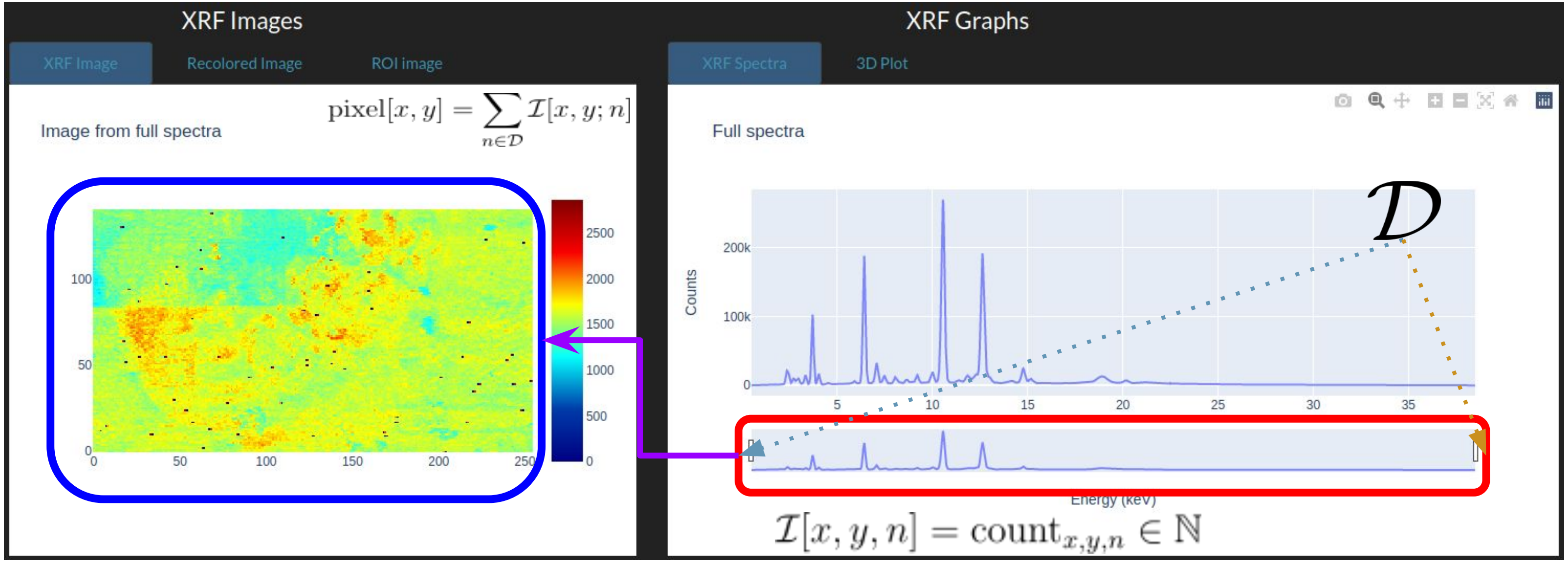

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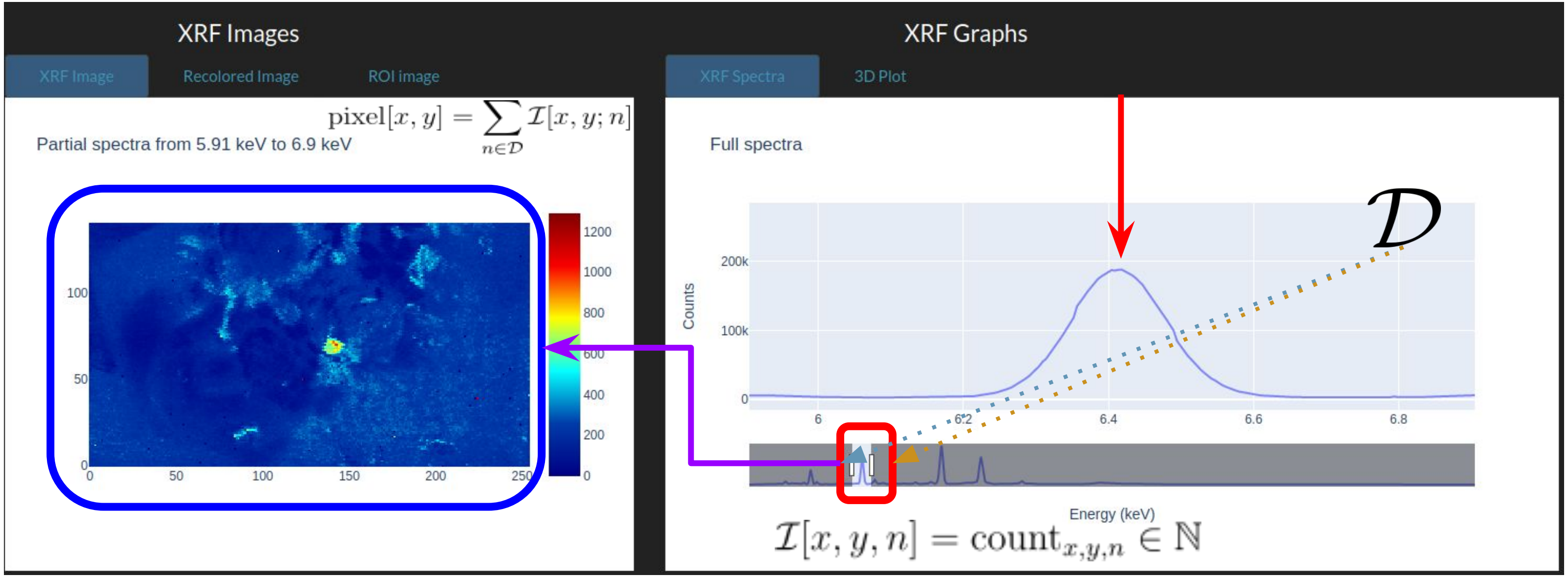
Kα Fe



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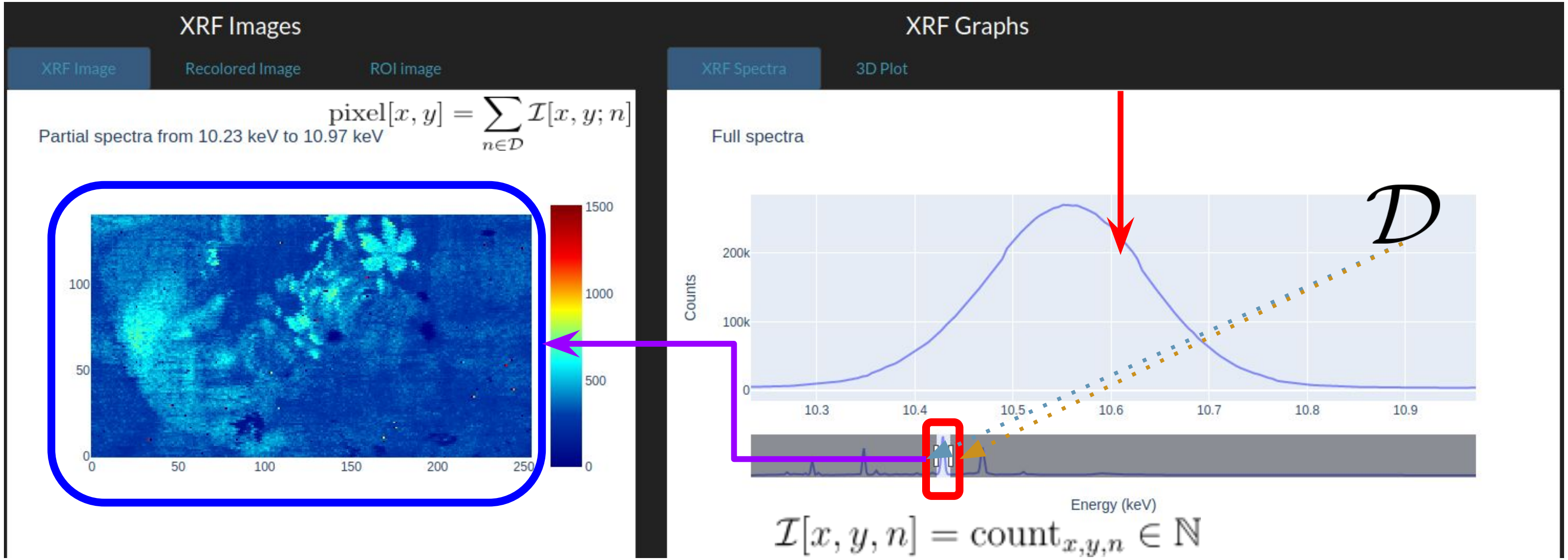
Kα Pb



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AIRES-CH
Neural Network Architectures

1D Branch

MORE DETAILS

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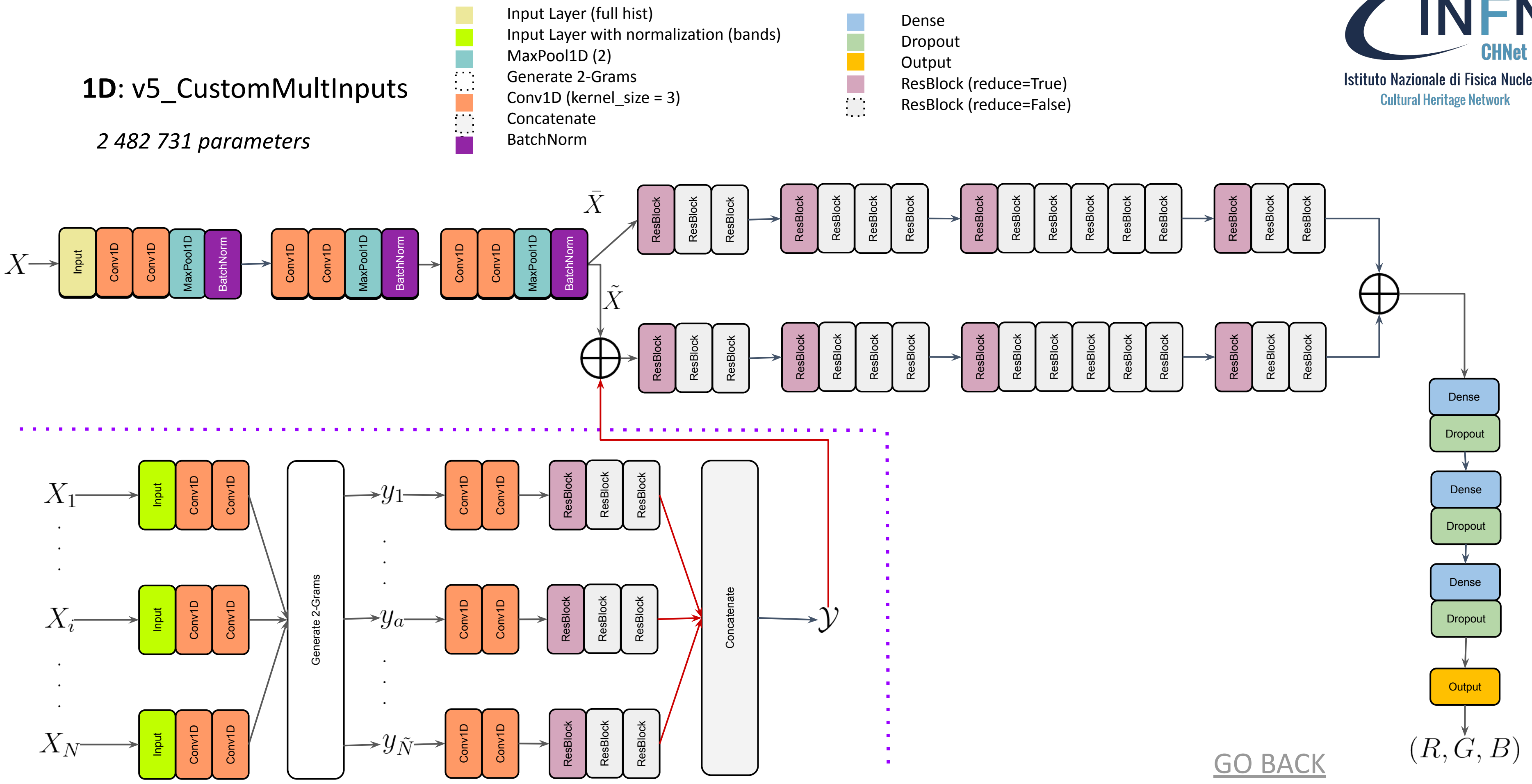
Cultural Heritage Network

1D: v5_CustomMultInputs

2 482 731 parameters



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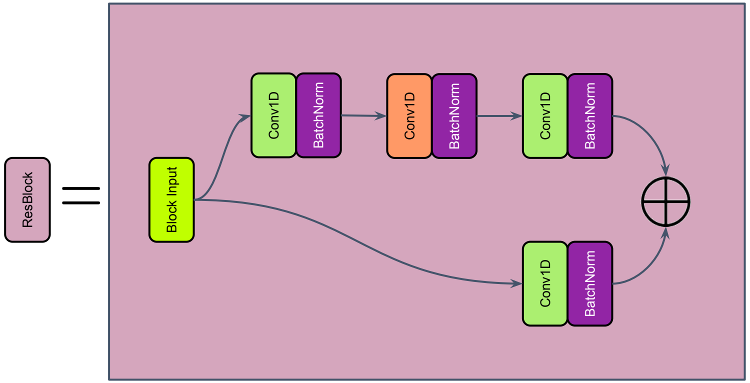
INFN CHNet Istituto Nazionale di Fisica Nucleare Cultural Heritage Network

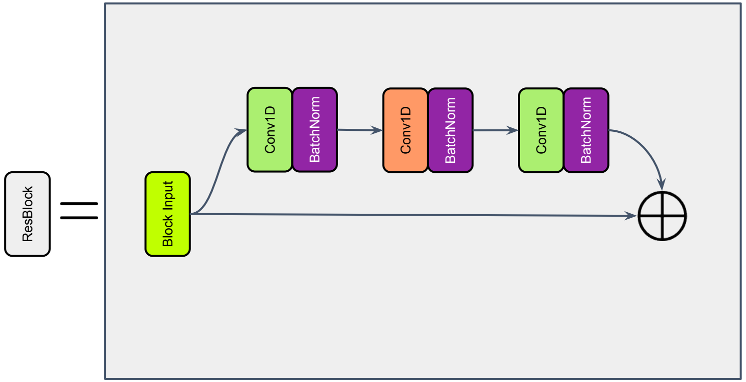
1D: v5_CustomMultInputs

- Input Layer (full hist)
- Input Layer with normalization (bands)
- MaxPool1D (2)
- Generate 2-Grams
- Conv1D (kernel_size = 3)
- Concatenate
- BatchNorm
- Dense
- Dropout
- Output
- Conv1D (kernel_size = 1)

Projection residual block



Identity residual block



Residual connections prevents Vanishing Gradient problem

$$x \mapsto f(x) + x$$

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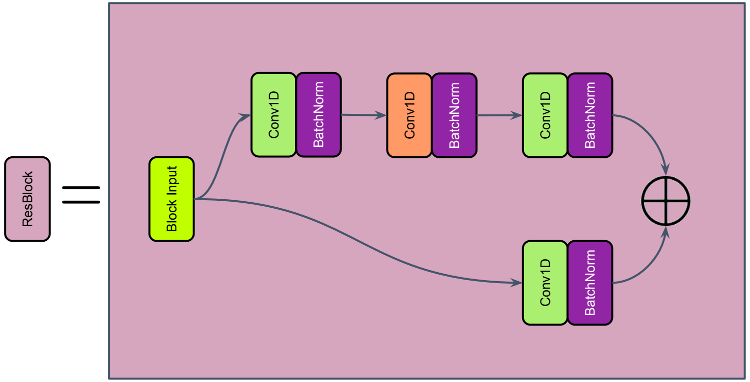
Cultural Heritage Network

1D: v5_CustomMultInputs

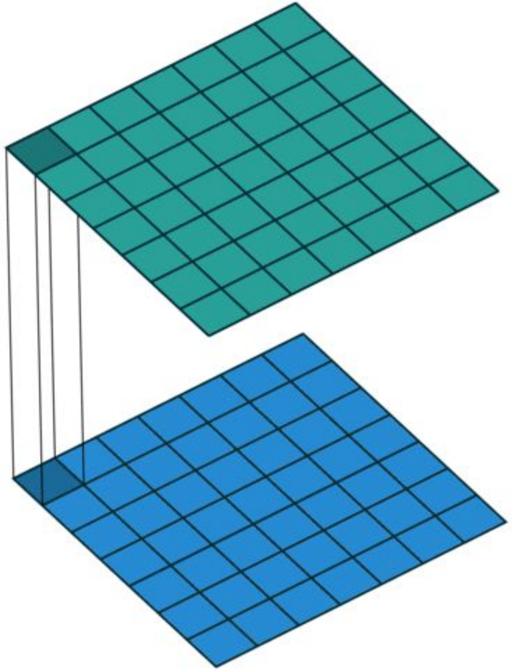
- Input Layer (full hist)
- Input Layer with normalization (bands)
- MaxPool1D (2)
- Generate 2-Grams
- Conv1D (kernel_size = 3)
- Concatenate
- BatchNorm
- Dense
- Dropout
- Output
- Conv1D (kernel_size = 1)

Projection residual block



Most simplistic explanation would be that 1x1 convolution leads to dimension reductionality. For example, an image of 200 x 200 with 50 features on convolution with 20 filters of 1x1 would result in size of 200 x 200 x 20.

A 1x1xU convolution filter convolved across a V-channel image emulates a UxV matrix multiplied by each V-channel pixel, which is the same as running a single-layer neural network across every pixel of your input as if each pixel were an example vector in a training set.



GO BACK

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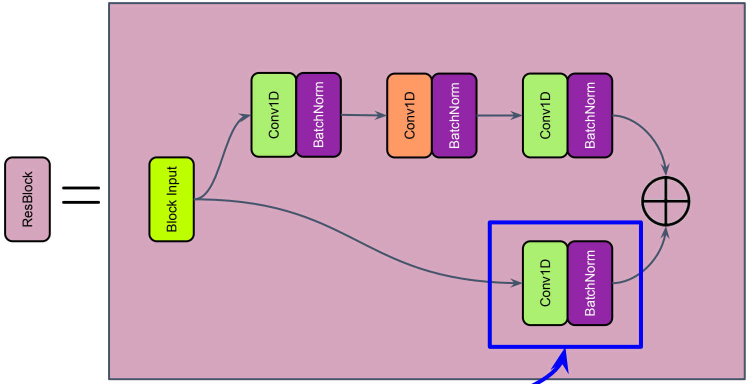
1D: v5_CustomMultInputs

- Input Layer (full hist)
- Input Layer with normalization (bands)
- MaxPool1D (2)
- Generate 2-Grams
- Conv1D (kernel_size = 3)
- Concatenate
- BatchNorm
- Dense
- Dropout
- Output
- Conv1D (kernel_size = 1)

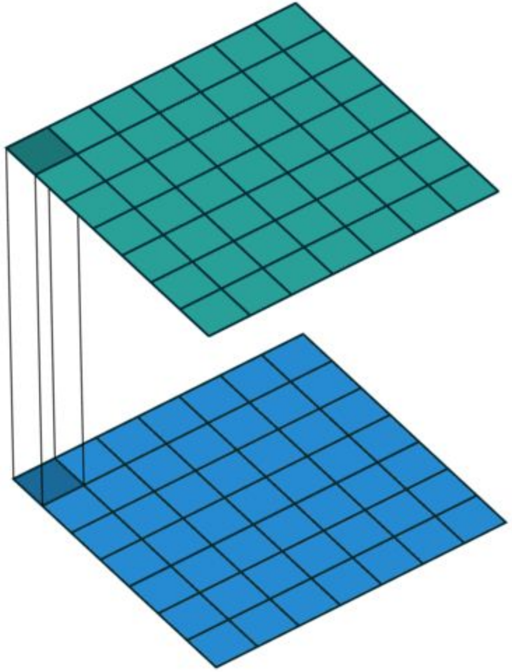
Projection residual block



Reduce size
(in filters' number direction)

Most simplistic explanation would be that 1x1 convolution leads to dimension reductionality. For example, an image of 200 x 200 with 50 features on convolution with 20 filters of 1x1 would result in size of 200 x 200 x 20.

A 1x1xU convolution filter convolved across a V-channel image emulates a UxV matrix multiplied by each V-channel pixel, which is the same as running a single-layer neural network across every pixel of your input as if each pixel were an example vector in a training set.



GO BACK

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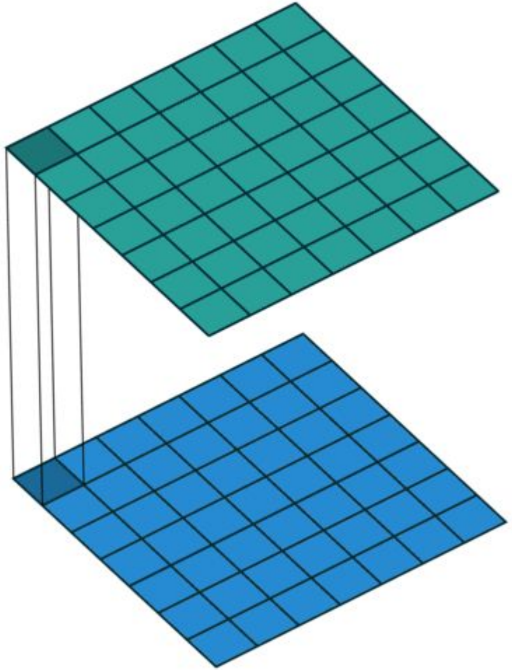
Cultural Heritage Network

1D: v5_CustomMultInputs

- Input Layer (full hist)
- Input Layer with normalization (bands)
- MaxPool1D (2)
- Generate 2-Grams
- Conv1D (kernel_size = 3)
- Concatenate
- BatchNorm
- Dense
- Dropout
- Output
- Conv1D (kernel_size = 1)



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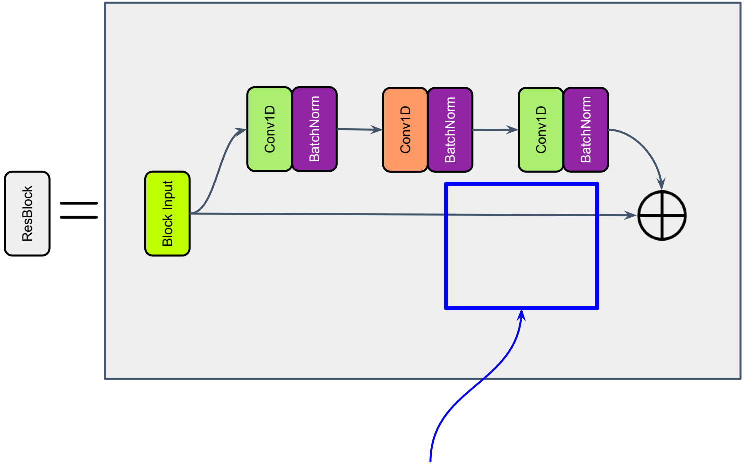
A 1x1xU convolution filter convolved across a V-channel image emulates a UxV matrix multiplied by each V-channel pixel, which is the same as running a single-layer neural network across every pixel of your input as if each pixel were an example vector in a training set.

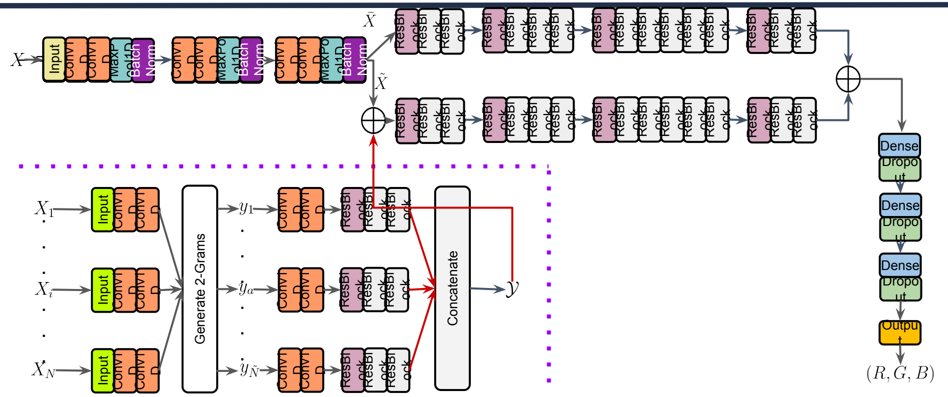
Identity residual block



Doesn’t reduce size
(in filters’ number direction)
= Pure identity

GO BACK

1D: v5_CustomMultInputs
RESULTS



SCORES

The higher, the better:
SSIM mean on 8 test images for model v5_CustomMultInputs test images: **0.38844215869903564**
MS-SSIM mean on 8 test images for model v5_CustomMultInputs test images: **0.6803240776062012**
PSNR mean on 8 test images for model v5_CustomMultInputs test images: **20.103897094726562**

The lower, the better:
BCE mean on 8 test images for model v5_CustomMultInputs test images: **0.636454114069541З**
MSE mean on 8 test images for model v5_CustomMultInputs test images: **0.013798782990003625**

GO BACK

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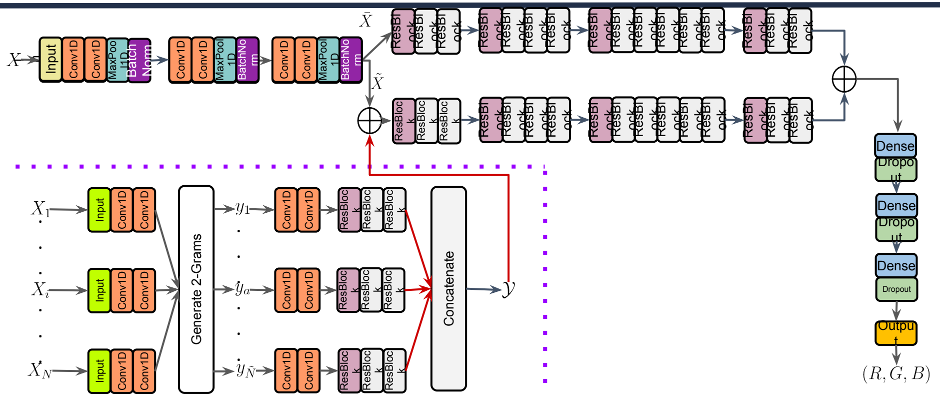
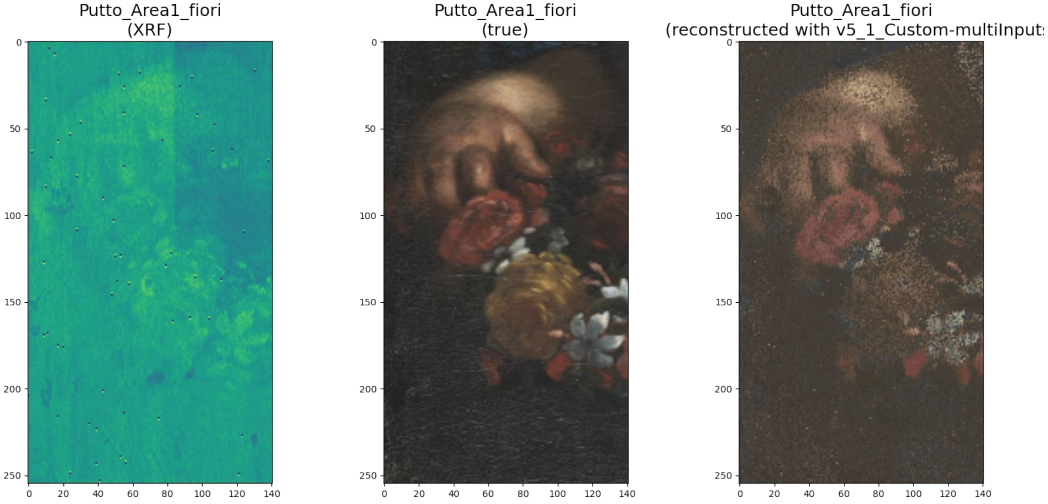
1D: v5_CustomMultInputs
RESULTS





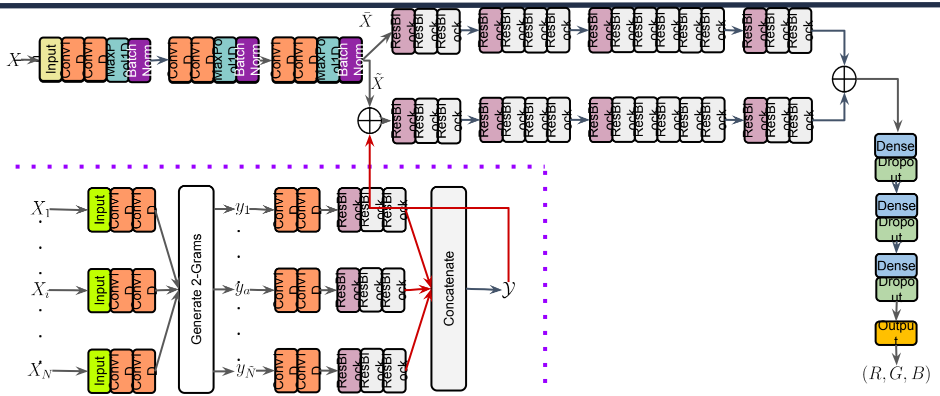
Model parameters: 2482731
Losses: SSIM=0.497; MS-SSIM=0.84; PSNR=22.048; BCE=0.6; MSE=0.006;

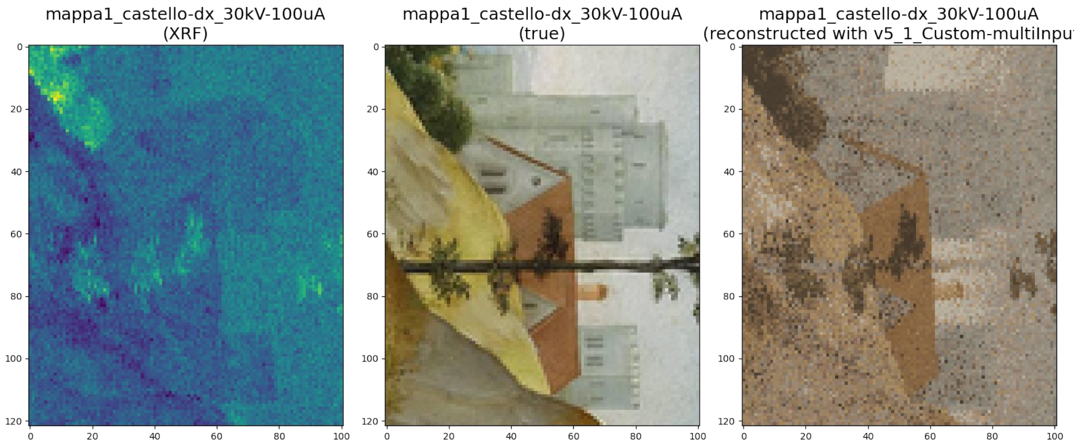
GOOD

GO BACK

INFN CHNet
Istituto Nazionale di Fisica Nucleare
Cultural Heritage Network

1D: v5_CustomMultInputs
RESULTS





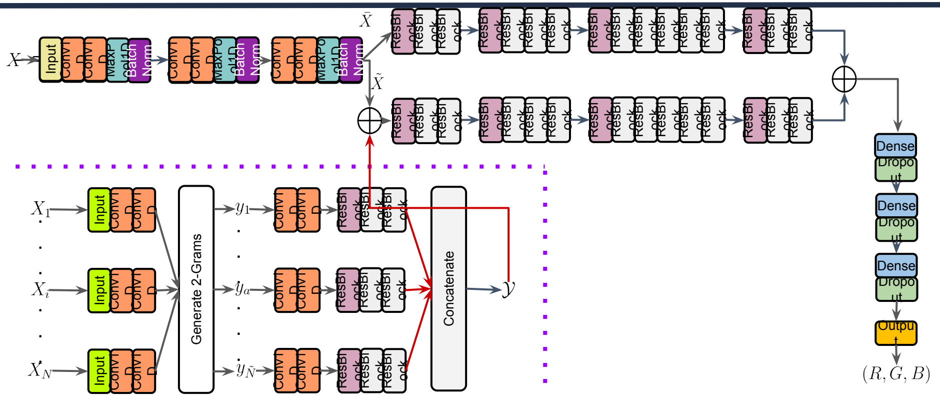
Model parameters: 2482731
Losses: SSIM=0.35; MS-SSIM=0.744; PSNR=17.124; BCE=0.71; MSE=0.019;

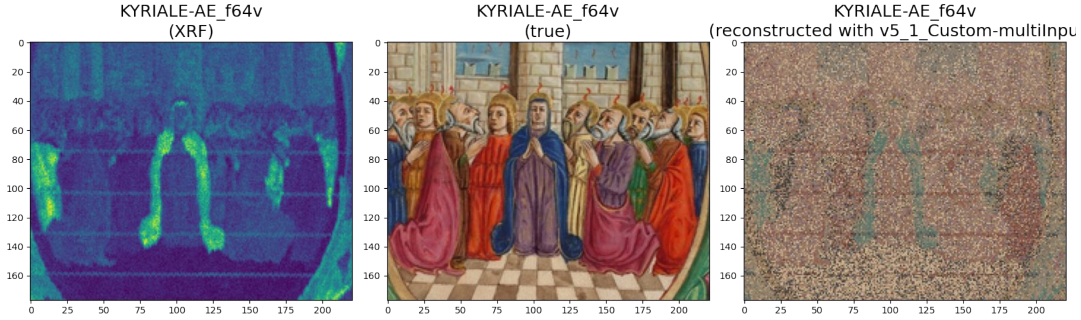
GOOD

GO BACK

1D: v5_CustomMultInputs

RESULTS



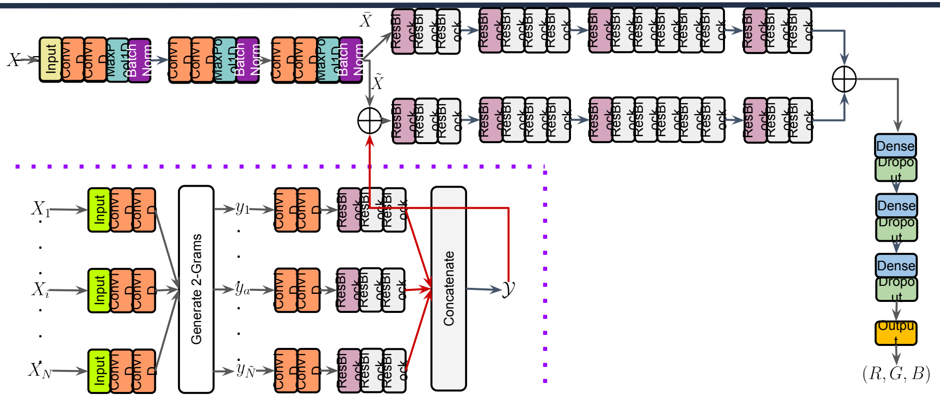


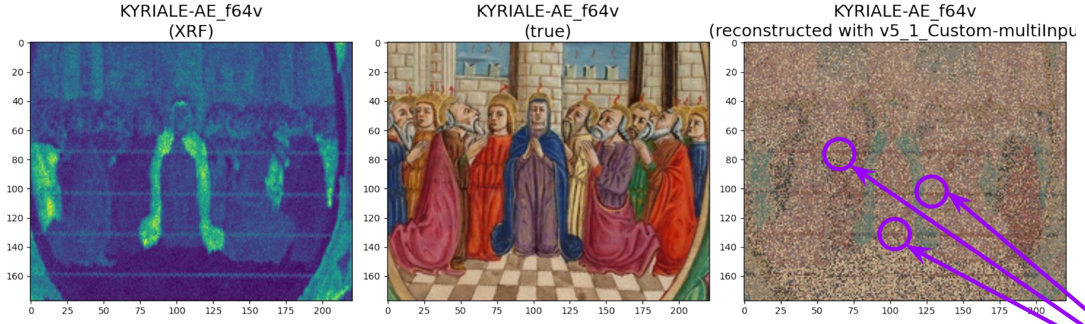
Model parameters: 2482731
Losses: SSIM=0.058; MS-SSIM=0.209; PSNR=13.816; BCE=0.767; MSE=0.042;

NO GOOD

GO BACK

1D: v5_CustomMultInputs
RESULTS





Model parameters: 2482731
Losses: SSIM=0.058; MS-SSIM=0.209; PSNR=13.816; BCE=0.767; MSE=0.042;

NO GOOD

Pentagram drawn in the back page
XRF sees behind outermost pictorial layer
too many layers are difficult to recolor

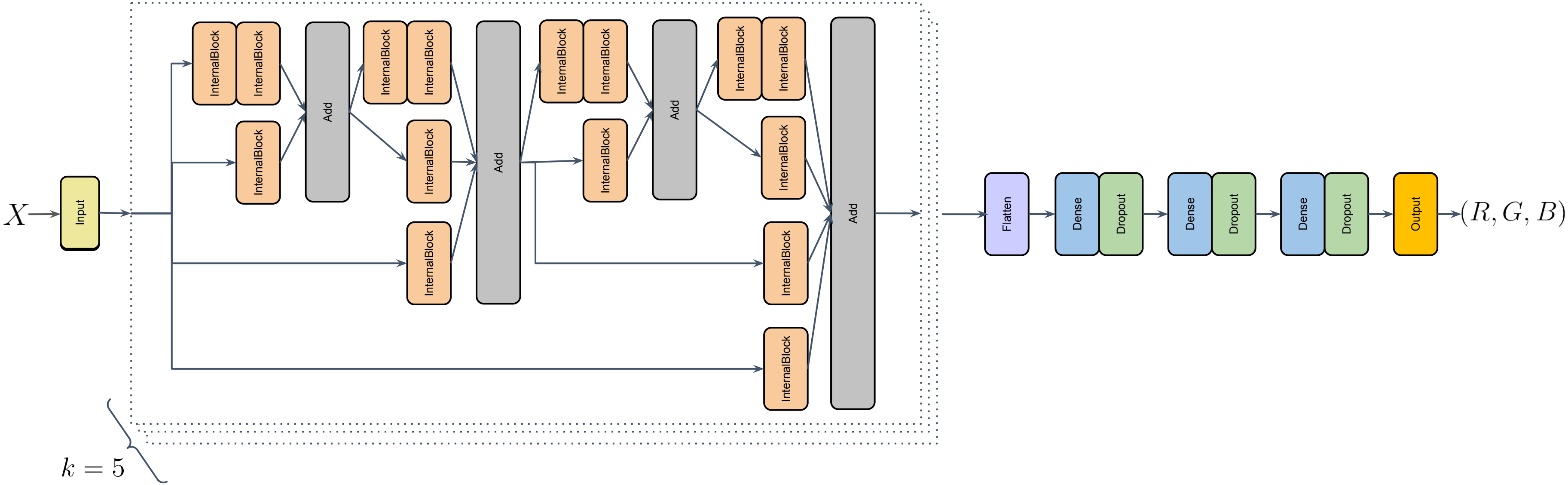
GO BACK

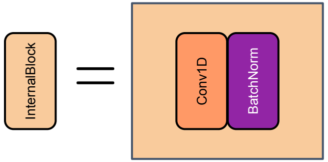
1D: v6_FractalNet

2 117 195 parameters

Input Layer (full hist)
MaxPool1D (2)
Fractal Block
Conv1D (kernel_size = 3)
BatchNorm

Dense
Dropout
Output
Internal block
Flatten

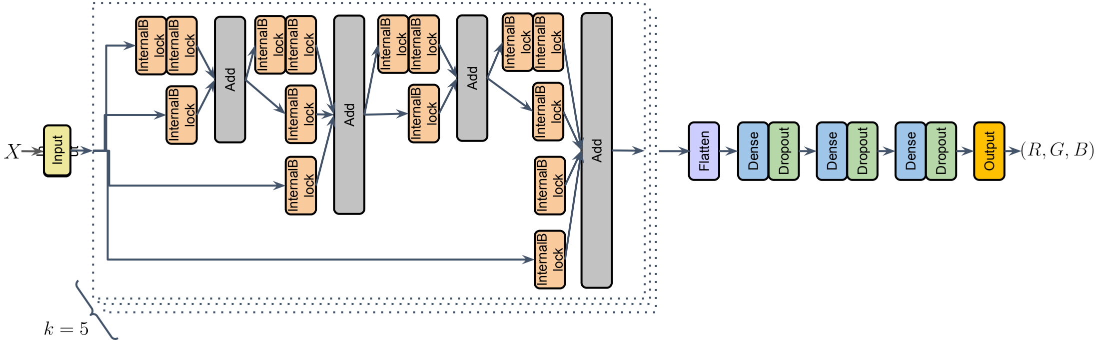




GO BACK

INFN CHNet Istituto Nazionale di Fisica Nucleare Cultural Heritage Network

1D: v6_FractalNet
RESULTS



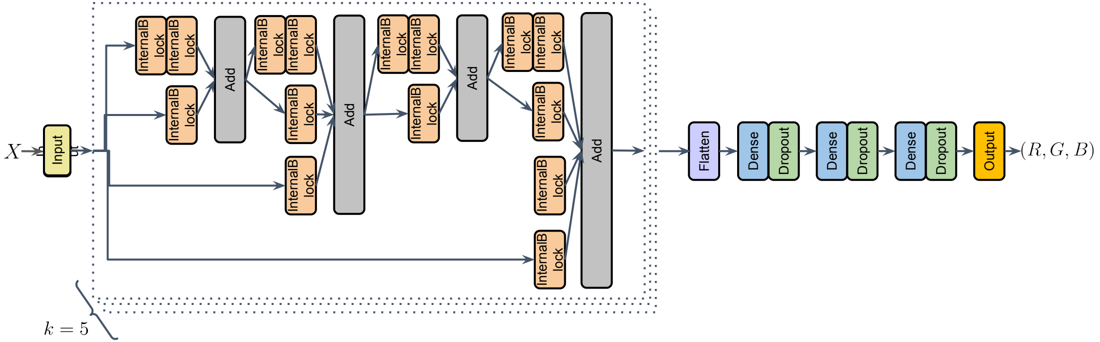
SCORES

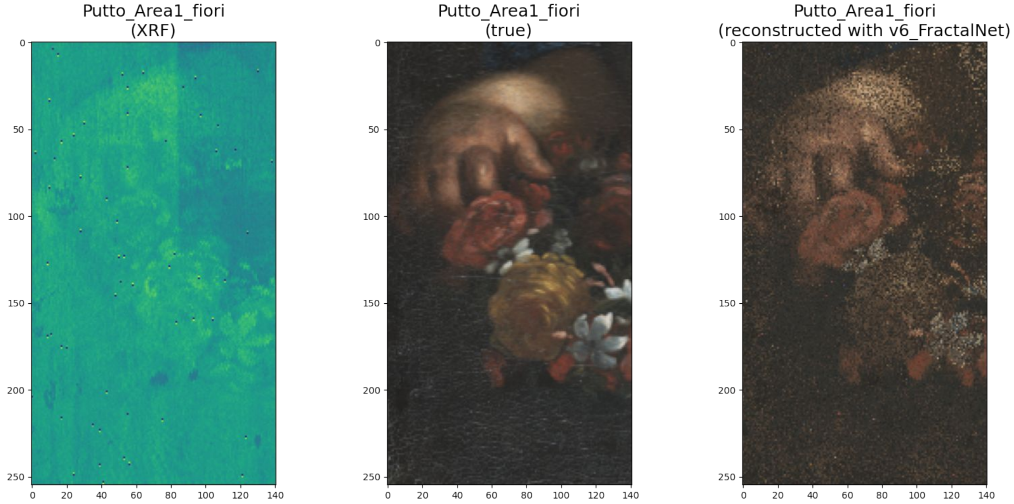
The higher, the better:
SSIM mean on 8 test images for model v6_FractalNet test images: **0.37207430601119995**
MS-SSIM mean on 8 test images for model v6_FractalNet test images: **0.6766429543495178**
PSNR mean on 8 test images for model v6_FractalNet test images: **20.075578689575195**

The lower, the better:
BCE mean on 8 test images for model v6_FractalNet test images: **0.6330596869811416**
MSE mean on 8 test images for model v6_FractalNet test images: **0.014069222259422531**

GO BACK

1D: v6_FractalNet
RESULTS



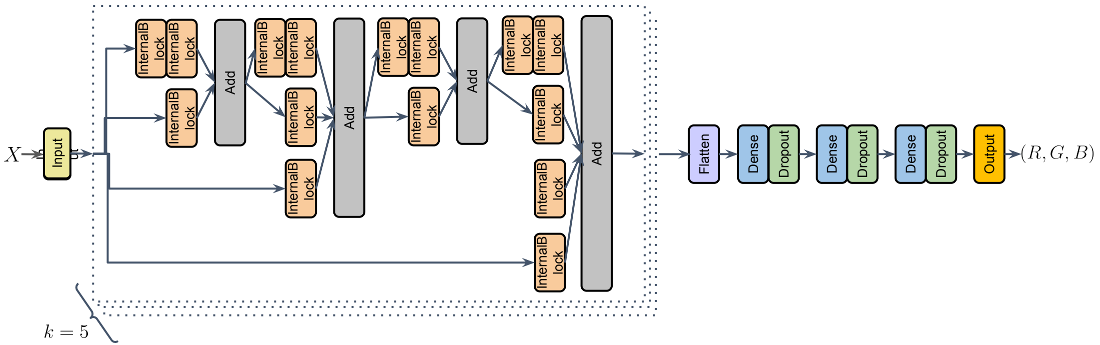


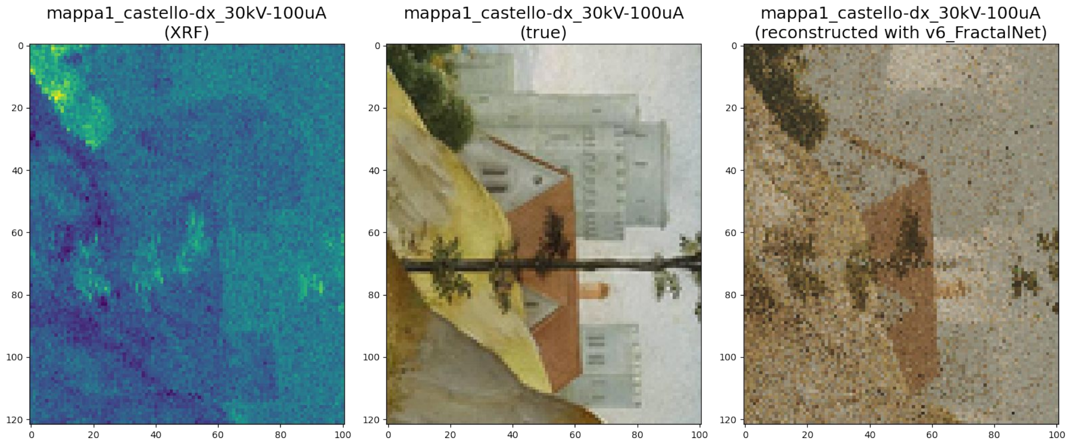
Model parameters: 2117195
Losses: SSIM=0.437; MS-SSIM=0.823; PSNR=23.253; BCE=0.543; MSE=0.005;

GOOD

GO BACK

1D: v6_FractalNet
RESULTS



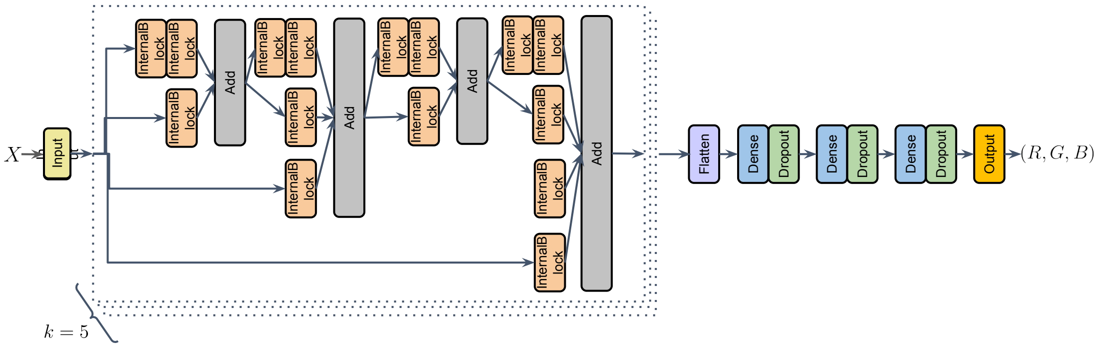


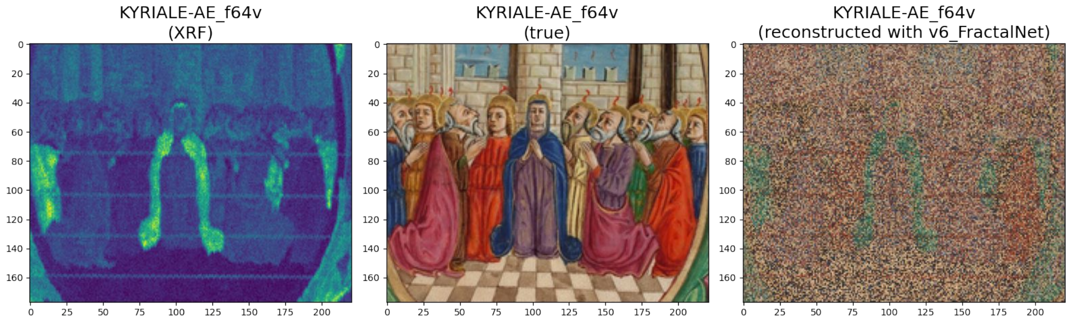
Model parameters: 2117195
Losses: SSIM=0.321; MS-SSIM=0.732; PSNR=16.942; BCE=0.705; MSE=0.02;

GOOD

GO BACK

1D: v6_FractalNet
RESULTS





Model parameters: 2117195
Losses: SSIM=0.041; MS-SSIM=0.202; PSNR=13.469; BCE=0.744; MSE=0.045;

NO GOOD

GO BACK

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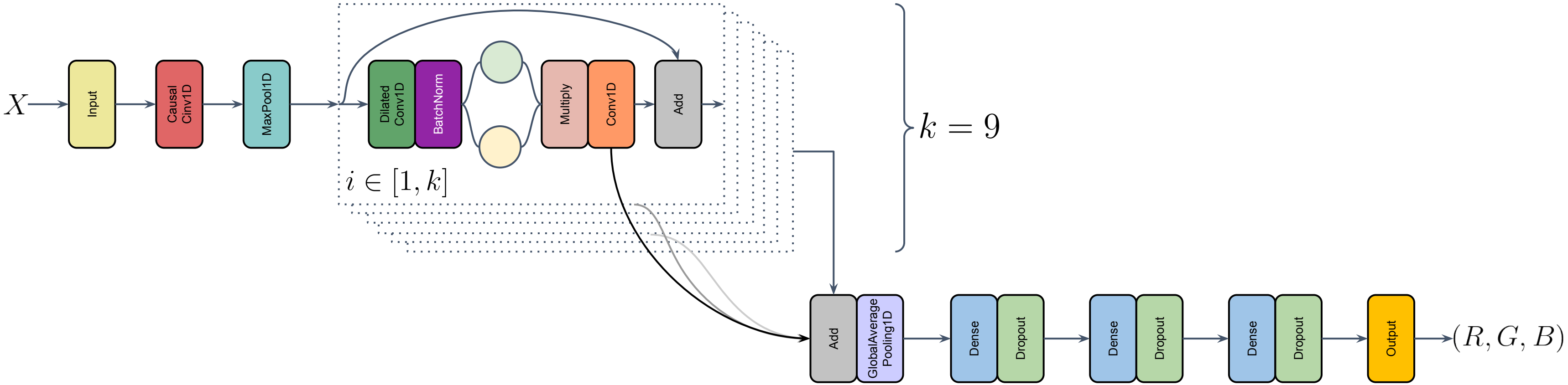
Cultural Heritage Network

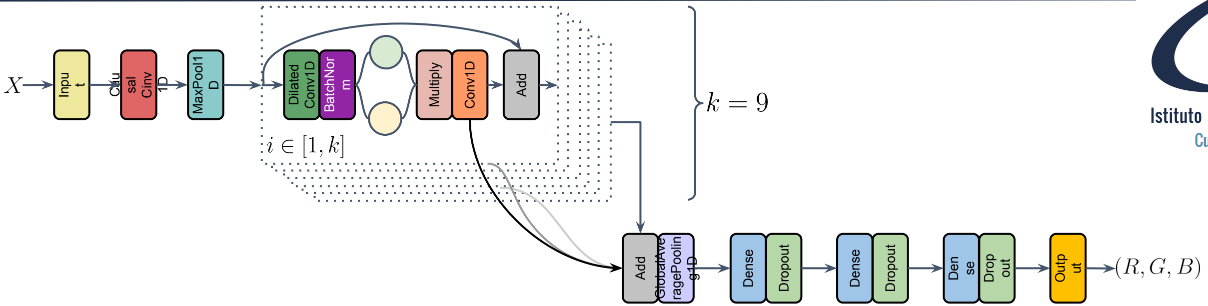
1D: v7_DilatedWaveNet

1 809 183 parameters

- Input Layer
- CausalConv (kernel_size = 3)
- MaxPool1D (2x2)
- WaveNet Block
- Conv1D (3)
- DilatedConv1D (3, dil_rate = $2 \cdot i$)
- BatchNorm
- Multiply
- Add
- GlobalAveragePooling1D
- Sigmoid Activation
- Tanh Activation
- Dense
- Dropout
- Output



GO BACK



1D: v7_DilatedWaveNet
RESULTS

SCORES

The higher, the better:
SSIM mean on 8 test images for model v7_WaveNet test images: **0.3563966155052185**
MS-SSIM mean on 8 test images for model v7_WaveNet test images: **0.6734365820884705**
PSNR mean on 8 test images for model v7_WaveNet test images: **19.979719161987305**

The lower, the better:
BCE mean on 8 test images for model v7_WaveNet test images: **0.6287169173359871**
MSE mean on 8 test images for model v7_WaveNet test images: **0.014554956532083451**

GO BACK

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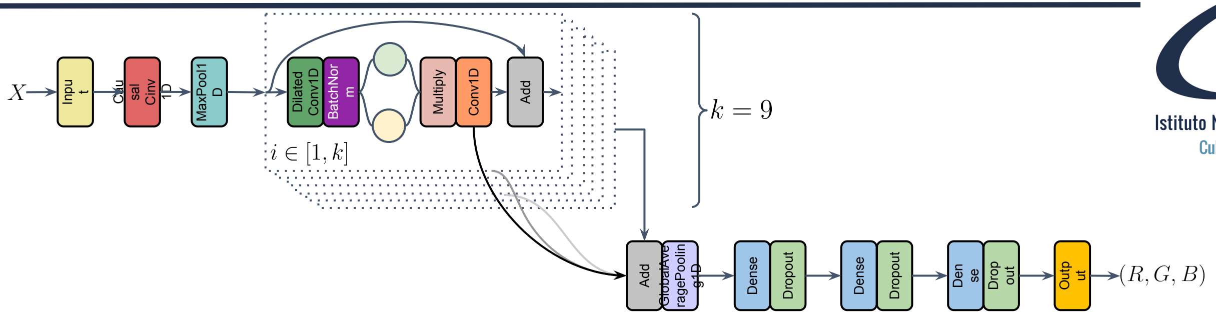
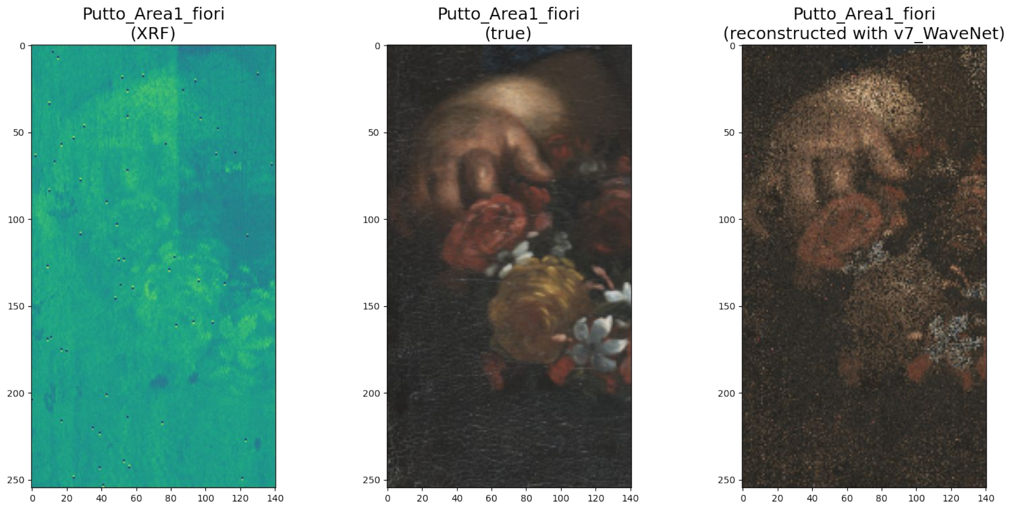
1D: v7_DilatedWaveNet
RESULTS



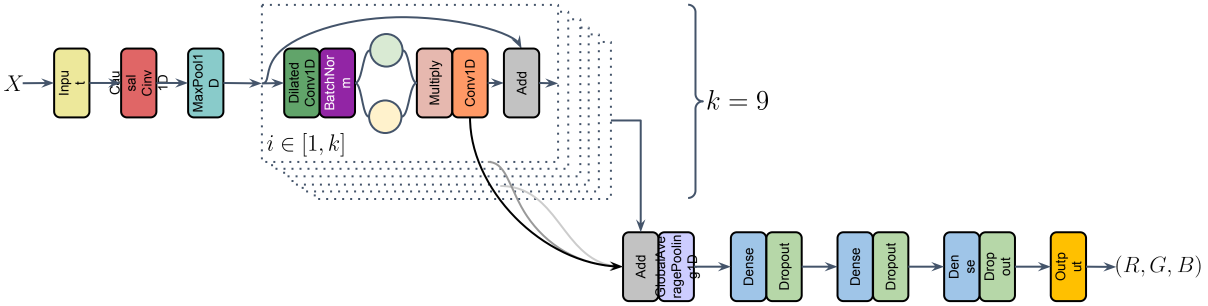


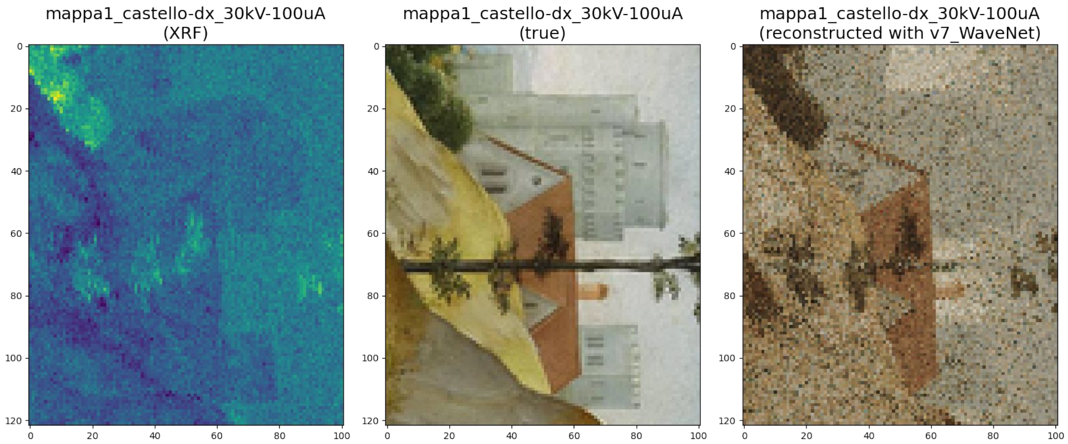
Model parameters: 1809183
Losses: SSIM=0.397; MS-SSIM=0.816; PSNR=23.101; BCE=0.532; MSE=0.005;

GOOD

GO BACK

1D: v7_DilatedWaveNet
RESULTS





Model parameters: 1809183
Losses: SSIM=0.277; MS-SSIM=0.734; PSNR=16.389; BCE=0.701; MSE=0.023;

GOOD

GO BACK

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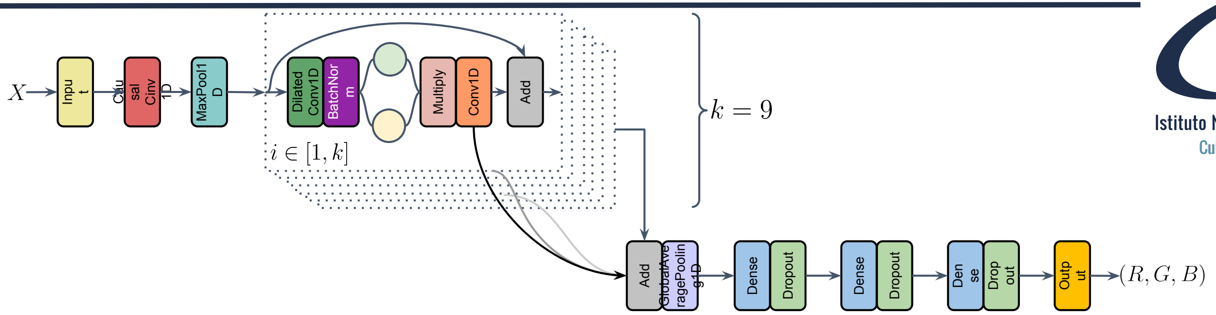
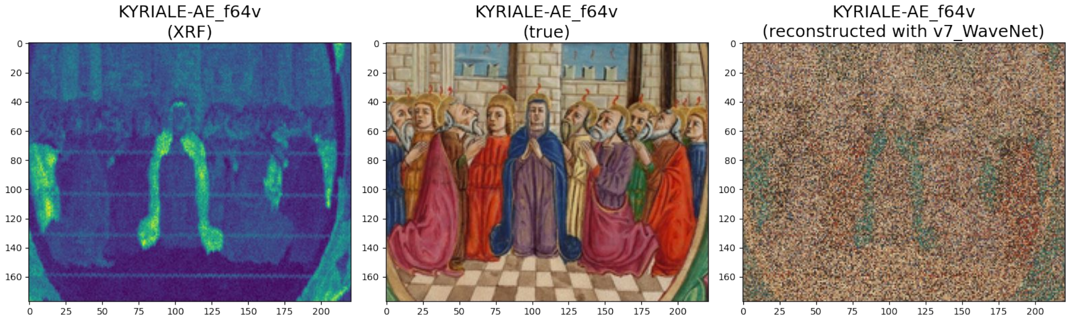
1D: v7_DilatedWaveNet
RESULTS





NO GOOD

Model parameters: 1809183
Losses: SSIM=0.041; MS-SSIM=0.21; PSNR=13.308; BCE=0.748; MSE=0.047;

GO BACK

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AIRES-CH

Neural Network Architectures

2D Branch

MORE DETAILS

GO BACK

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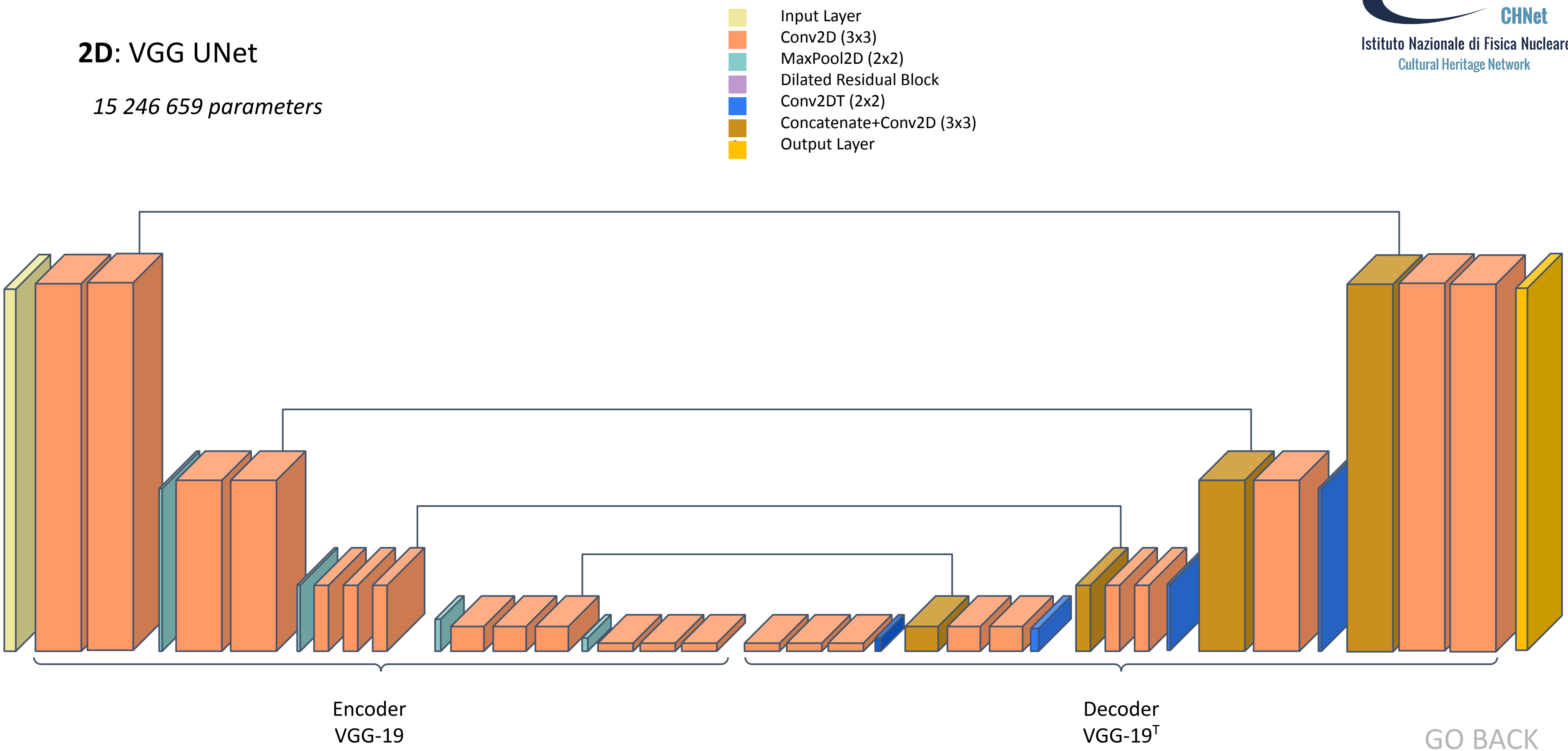
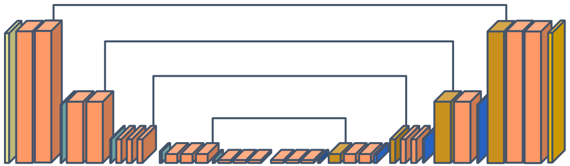
2D: VGG UNet

15 246 659 parameters

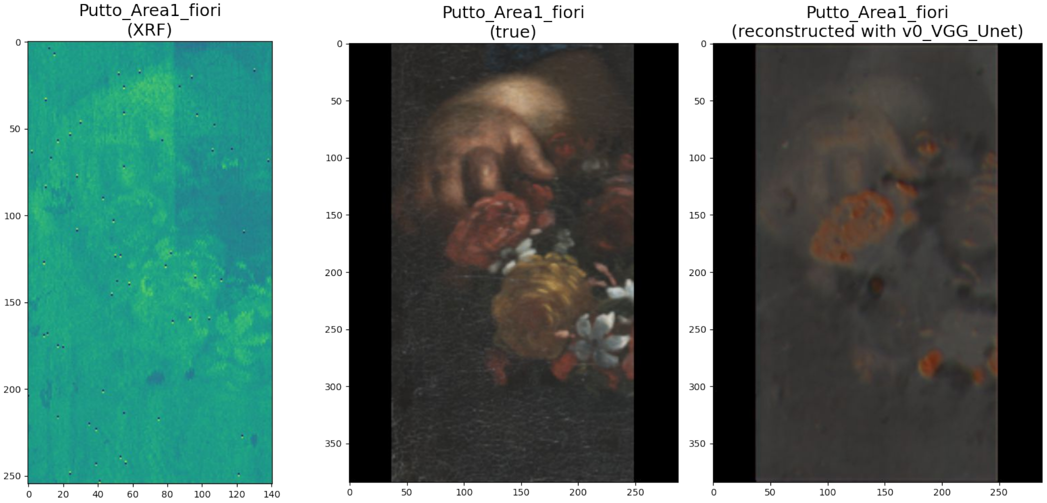


GO BACK



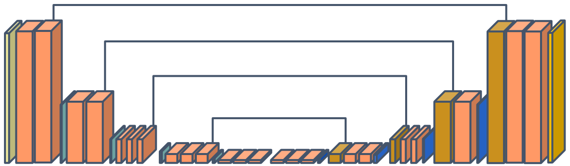
2D: VGG UNet

RESULTS

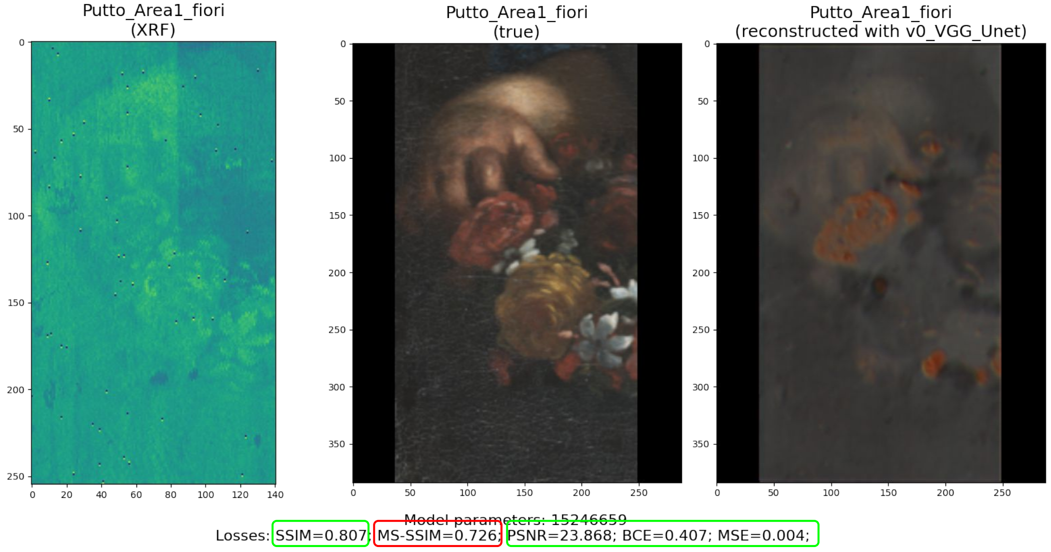


Model parameters: 15246659
Losses: SSIM=0.807; MS-SSIM=0.726; PSNR=23.868; BCE=0.407; MSE=0.004;

GO BACK



2D: VGG UNet
RESULTS



GO BACK

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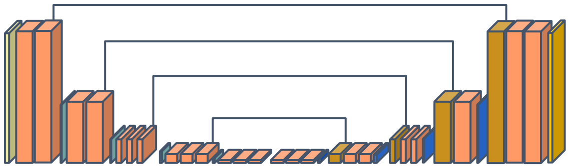
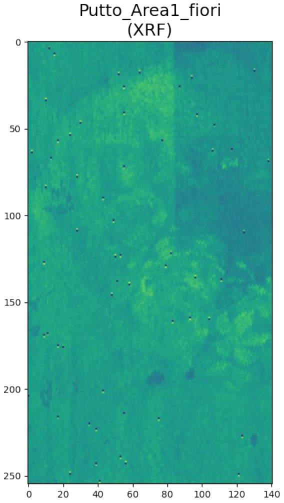
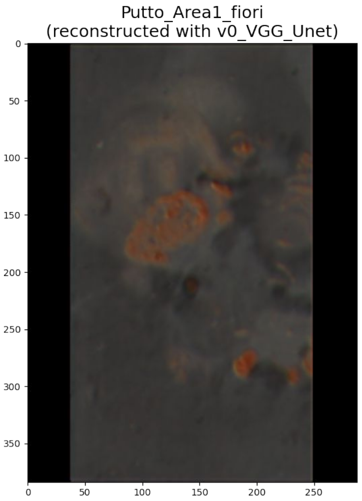
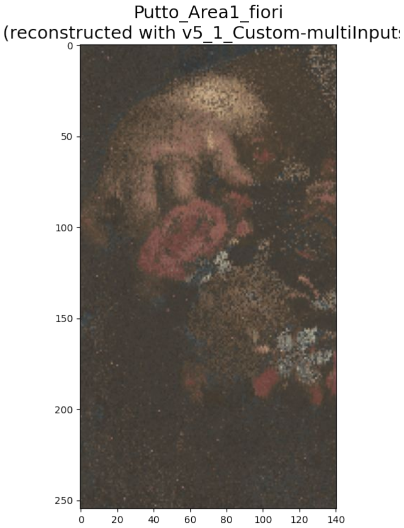


2D: VGG UNet
RESULTS







Model parameters: 15246659
Losses: SSIM=0.807; MS-SSIM=0.726; PSNR=23.868; BCE=0.407; MSE=0.004;

Model parameters: 2482731
Losses: SSIM=0.497; MS-SSIM=0.84; PSNR=22.048; BCE=0.6; MSE=0.006;

GO BACK

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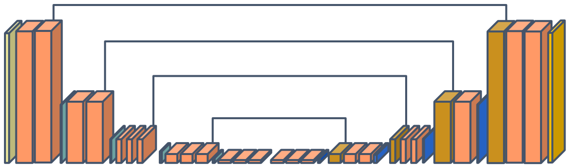
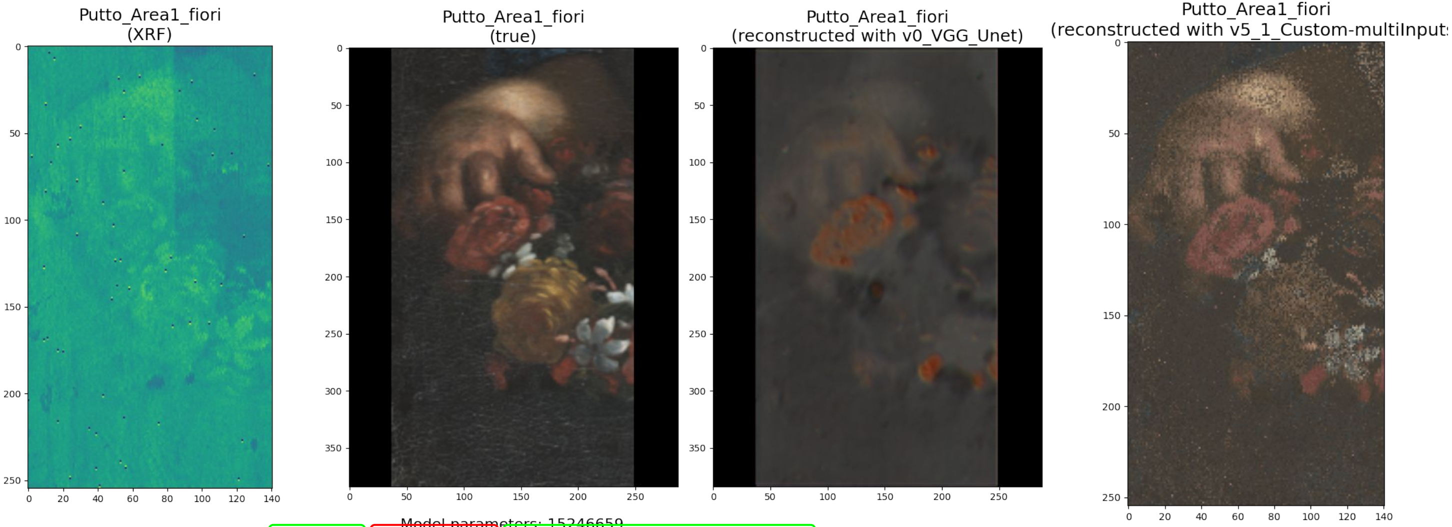
2D: VGG UNet
RESULTS



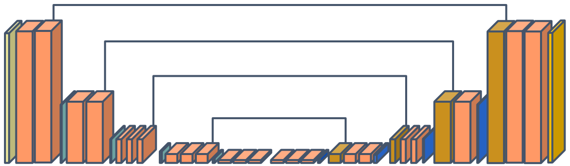


Model parameters: 15246659
Losses: SSIM=0.807; MS-SSIM=0.726; PSNR=23.868; BCE=0.407; MSE=0.004;

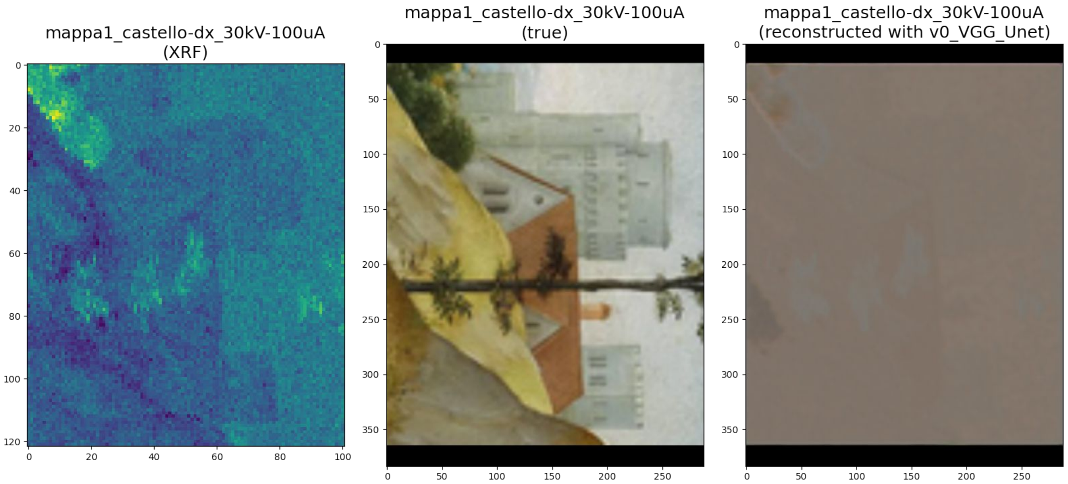
MS-SSIM most relevant metric

Model parameters: 2482731
Losses: SSIM=0.497; MS-SSIM=0.84; PSNR=22.048; BCE=0.6; MSE=0.006;

GO BACK



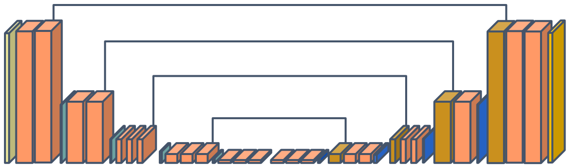
2D: VGG UNet
RESULTS



Model parameters: 15246659
Losses: SSIM=0.67; MS-SSIM=0.34; PSNR=14.666; BCE=0.701; MSE=0.034;

COMPLETE FAILURE
too many layers (?)

GO BACK



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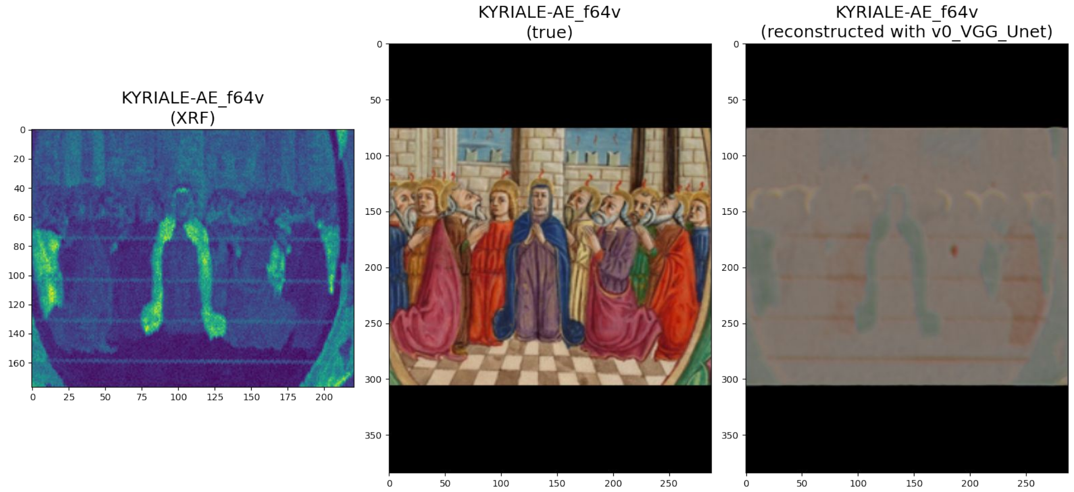
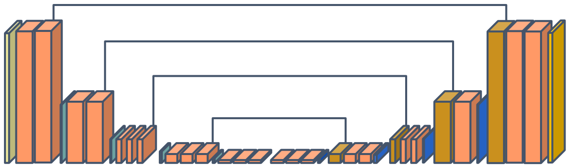
2D: VGG UNet
RESULTS



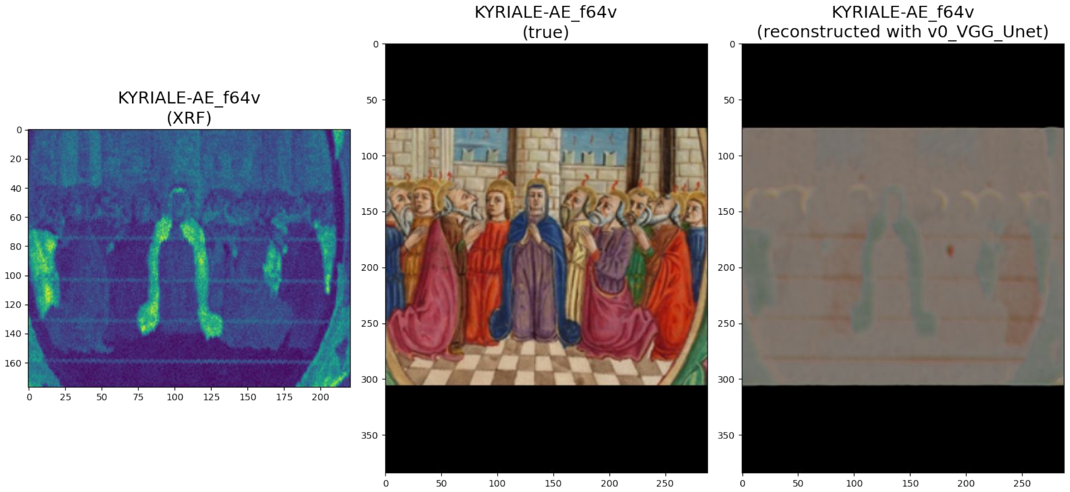
Model parameters: 15246659
Losses: SSIM=0.546; MS-SSIM=0.505; PSNR=17.381; BCE=0.465; MSE=0.018;

GO BACK

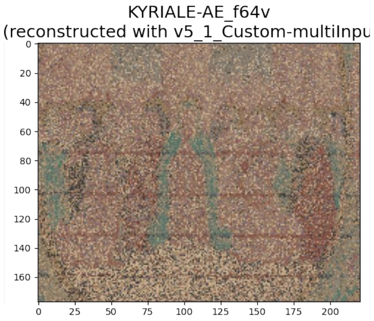


2D: VGG UNet

RESULTS

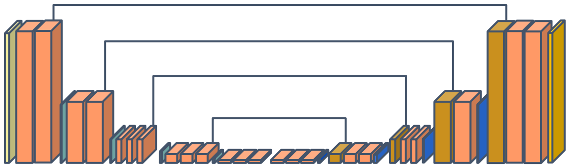


Model parameters: 15246659
Losses: SSIM=0.546; MS-SSIM=0.505; PSNR=17.381; BCE=0.465; MSE=0.018;

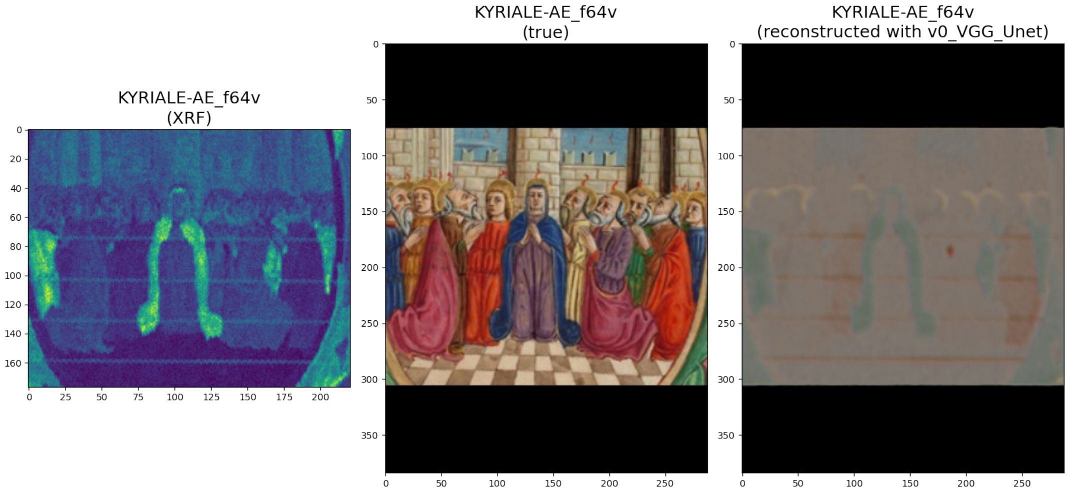


Model parameters: 2482731
Losses: SSIM=0.058; MS-SSIM=0.209; PSNR=13.816; BCE=0.767; MSE=0.042;

GO BACK



2D: VGG UNet
RESULTS



Model parameters: 15246659
Losses: SSIM=0.546; MS-SSIM=0.505; PSNR=17.381; BCE=0.465; MSE=0.018;

NOT SO BAD
why?

GO BACK

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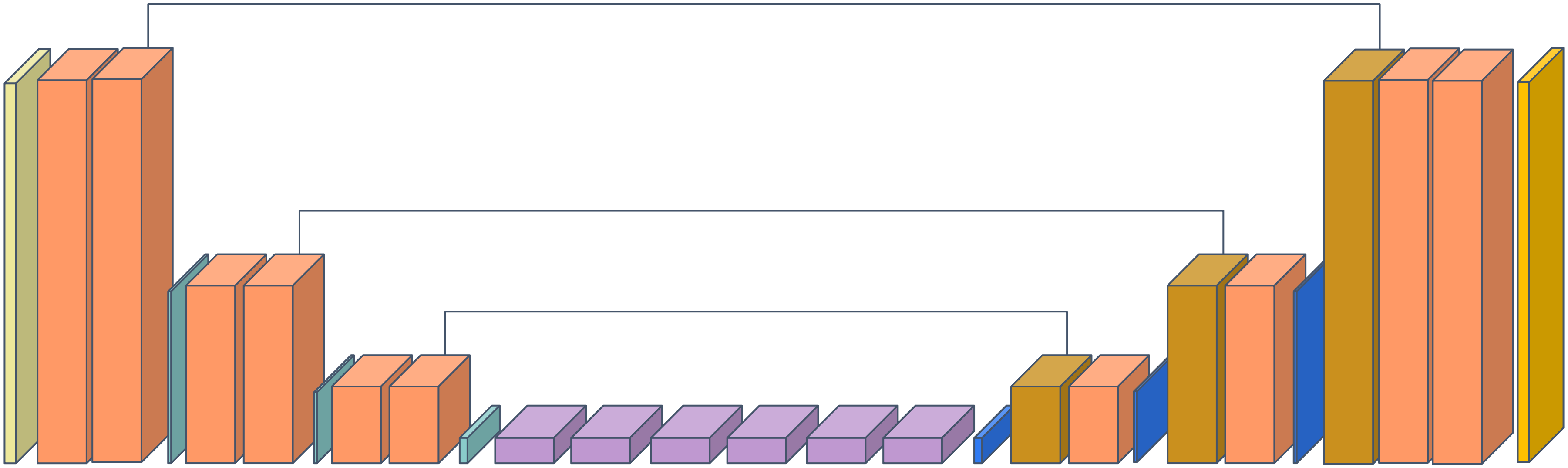
2D: Dilated Residual UNet

2 179 779 parameters

- Input Layer
- Conv2D (3x3)
- MaxPool2D (2x2)
- Dilated Residual Block
- Conv2DT (2x2)
- Concatenate+Conv2D (3x3)
- Output Layer



GO BACK

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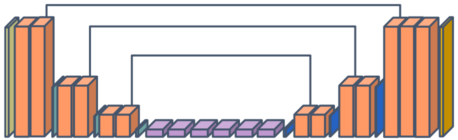
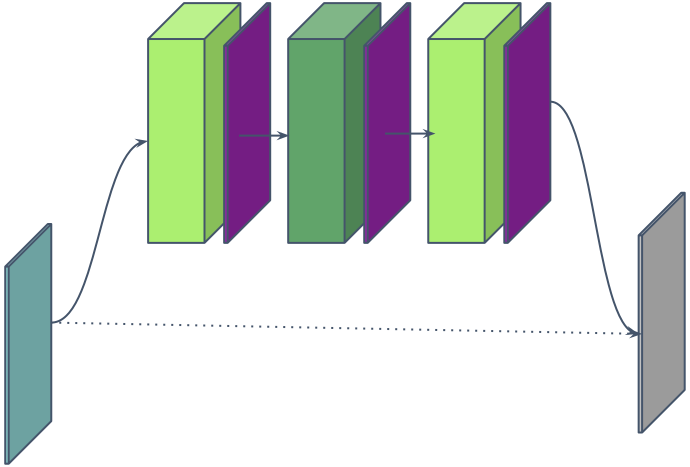


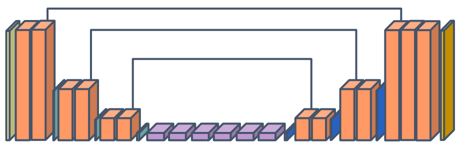
2D: Dilated Residual UNet

Dilated Residual Block



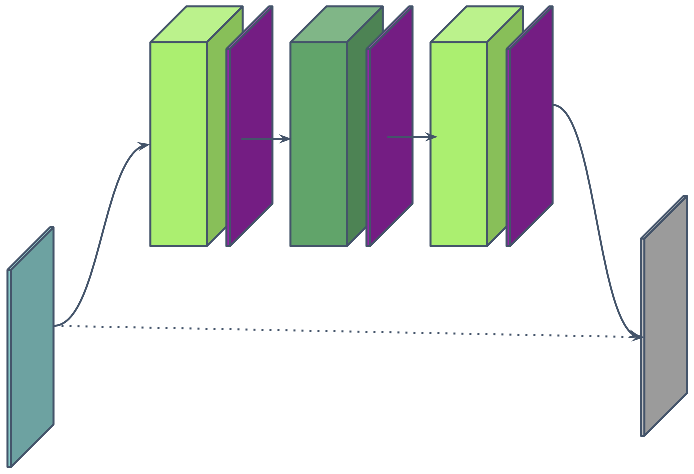
Block Input
Conv2D (1x1)
Dilated Conv2D (3x3)
BatchNorm
Add

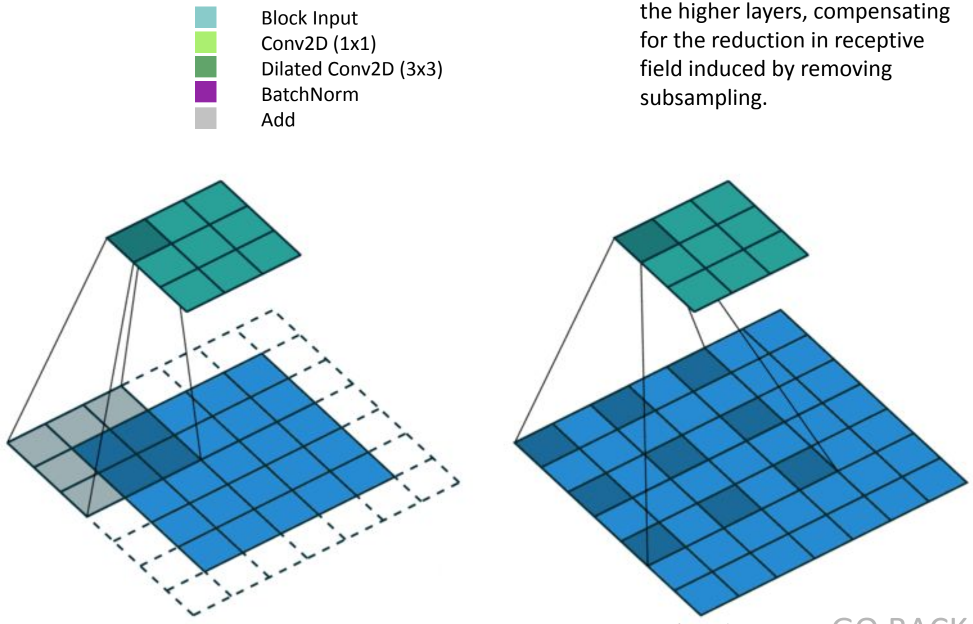
GO BACK



2D: Dilated Residual UNet

Dilated Residual Block

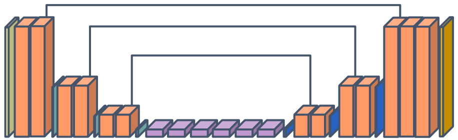


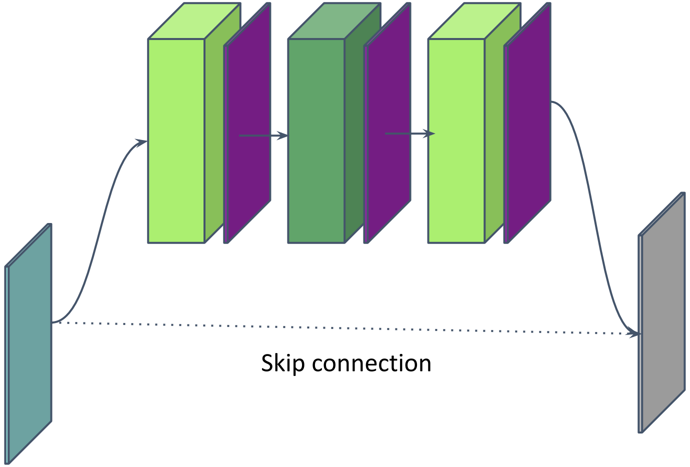


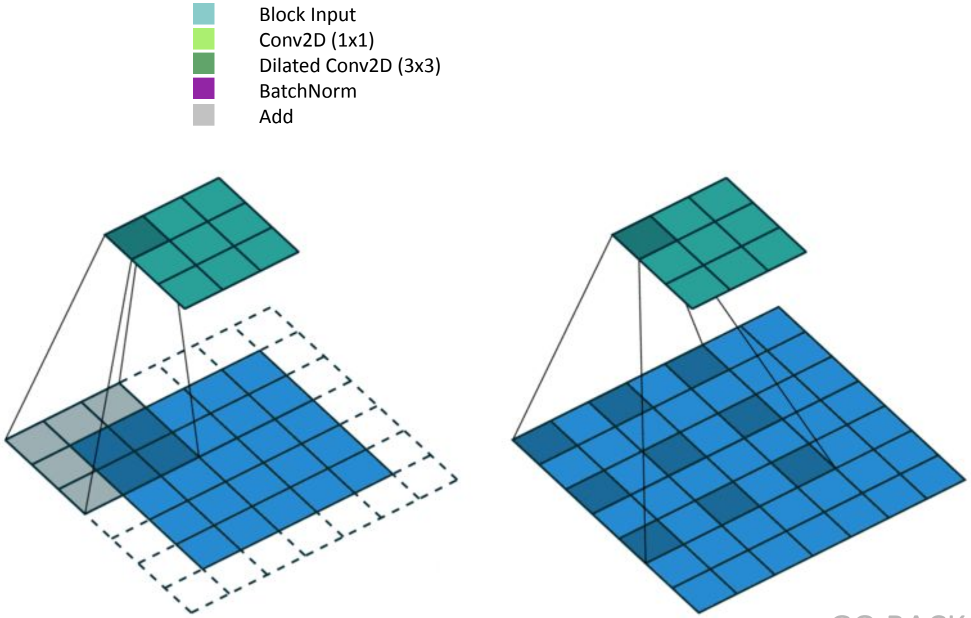
dilated convolutions are used to increase the receptive field of the higher layers, compensating for the reduction in receptive field induced by removing subsampling.

GO BACK

2D: Dilated Residual UNet
Dilated Residual Block







Residual connections prevents *Vanishing Gradient problem*

$$x \mapsto f(x) + x$$

GO BACK

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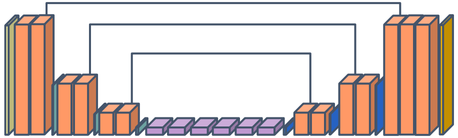
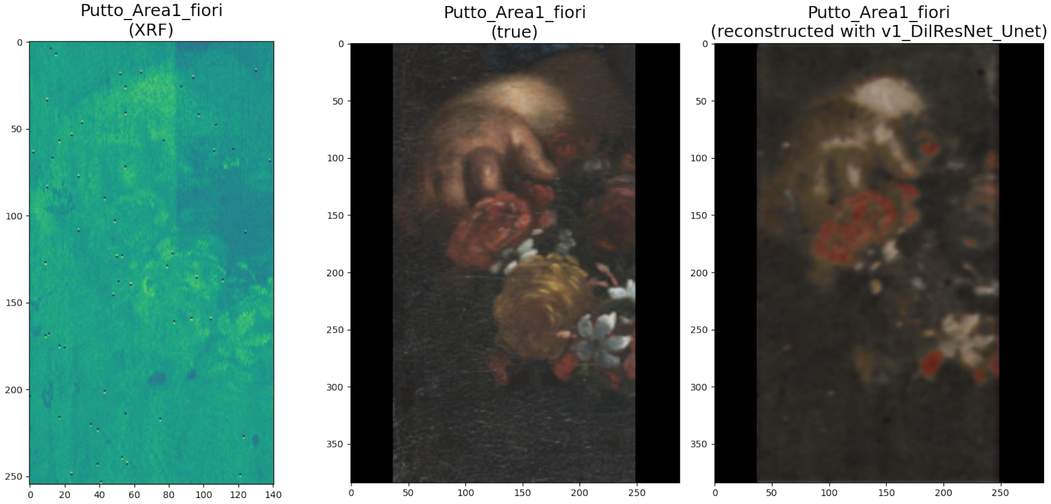


2D: Dilated Residual UNet
RESULTS



Model parameters: 2179779
Losses: SSIM=0.818; MS-SSIM=0.81; PSNR=25.529; BCE=0.366; MSE=0.002;

[GO BACK](#)

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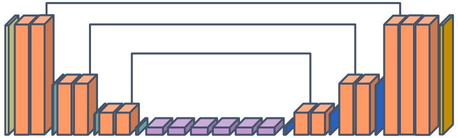
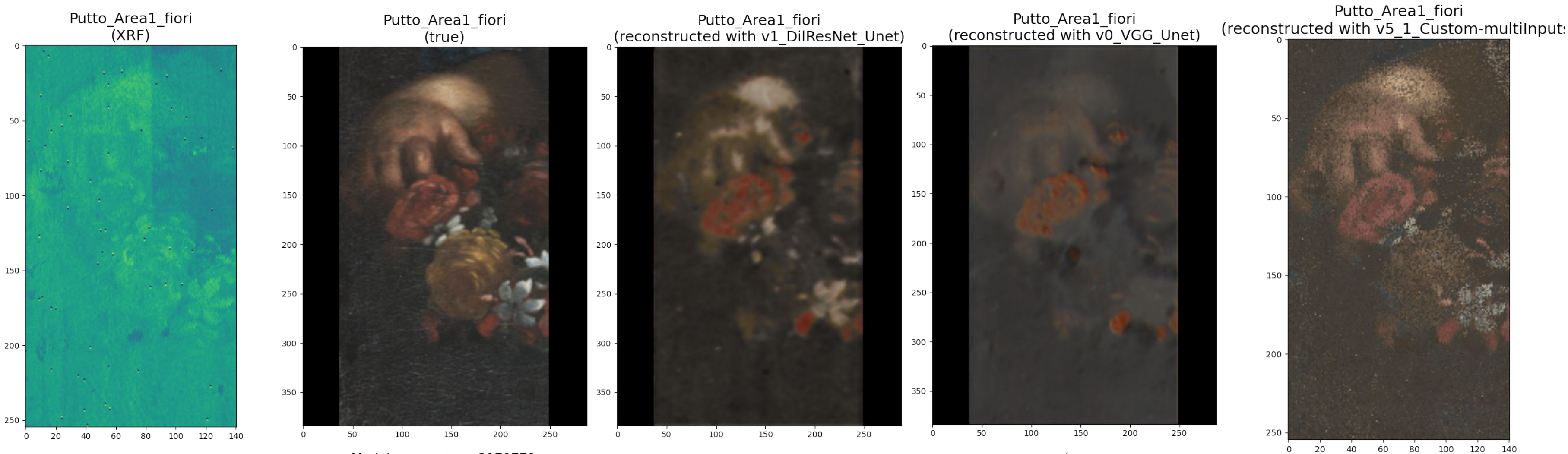
2D: Dilated Residual UNet
RESULTS



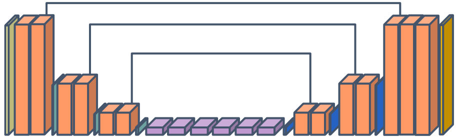


Model parameters: 2179779
Losses: SSIM=0.818; MS-SSIM=0.81; PSNR=25.529; BCE=0.366; MSE=0.002;

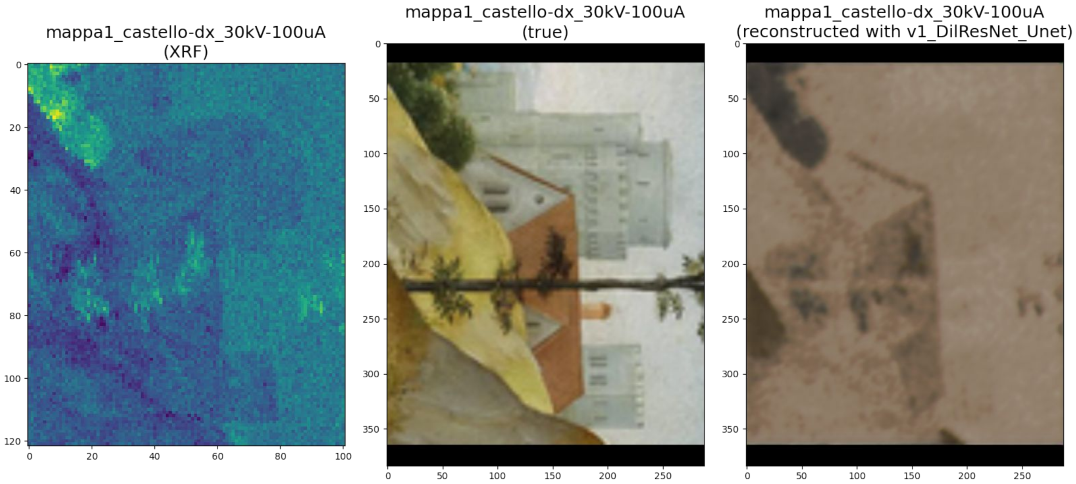
Model parameters: 15246659
Losses: SSIM=0.807; MS-SSIM=0.726; PSNR=23.868; BCE=0.407; MSE=0.004;

Model parameters: 2482731
Losses: SSIM=0.497; MS-SSIM=0.84; PSNR=22.048; BCE=0.6; MSE=0.006;

GO BACK



2D: Dilated Residual UNet
RESULTS

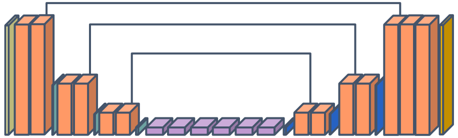


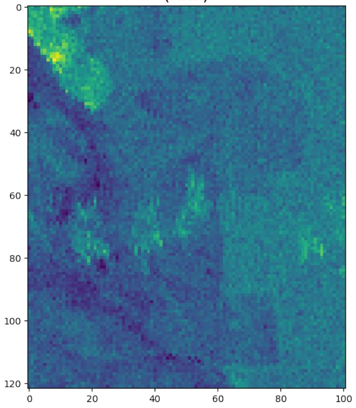
Model parameters: 2179779
Losses: SSIM=0.705; MS-SSIM=0.58; PSNR=16.283; BCE=0.66; MSE=0.023;

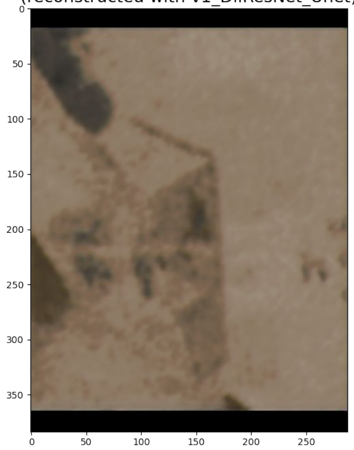
GO BACK

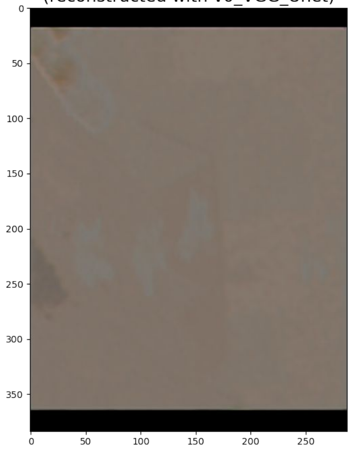
2D: Dilated Residual UNet

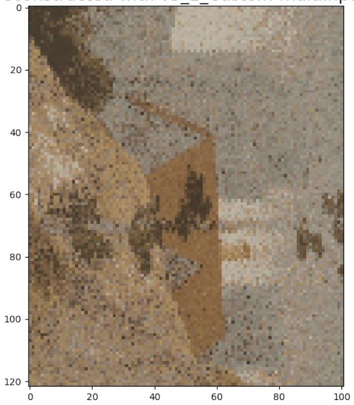
RESULTS











Model parameters: 2179779
Losses: SSIM=0.705; MS-SSIM=0.58; PSNR=16.283; BCE=0.66; MSE=0.023;

Model parameters: 15246659
Losses: SSIM=0.67; MS-SSIM=0.34; PSNR=14.666; BCE=0.701; MSE=0.034;

Model parameters: 2482731
Losses: SSIM=0.35; MS-SSIM=0.744; PSNR=17.124; BCE=0.71; MSE=0.019;

GO BACK

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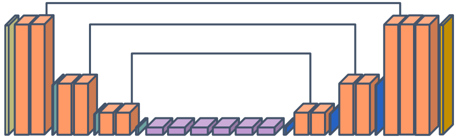
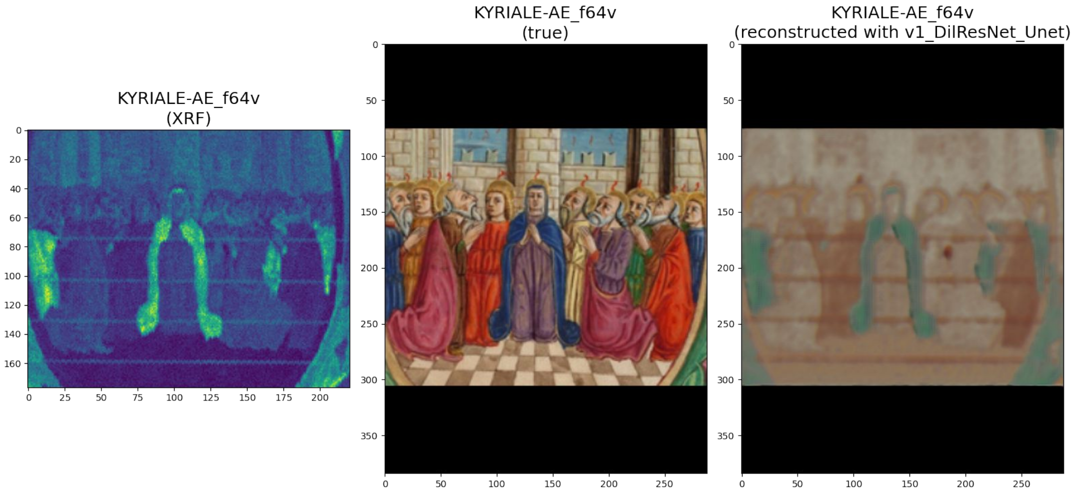
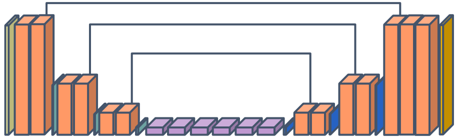


2D: Dilated Residual UNet
RESULTS



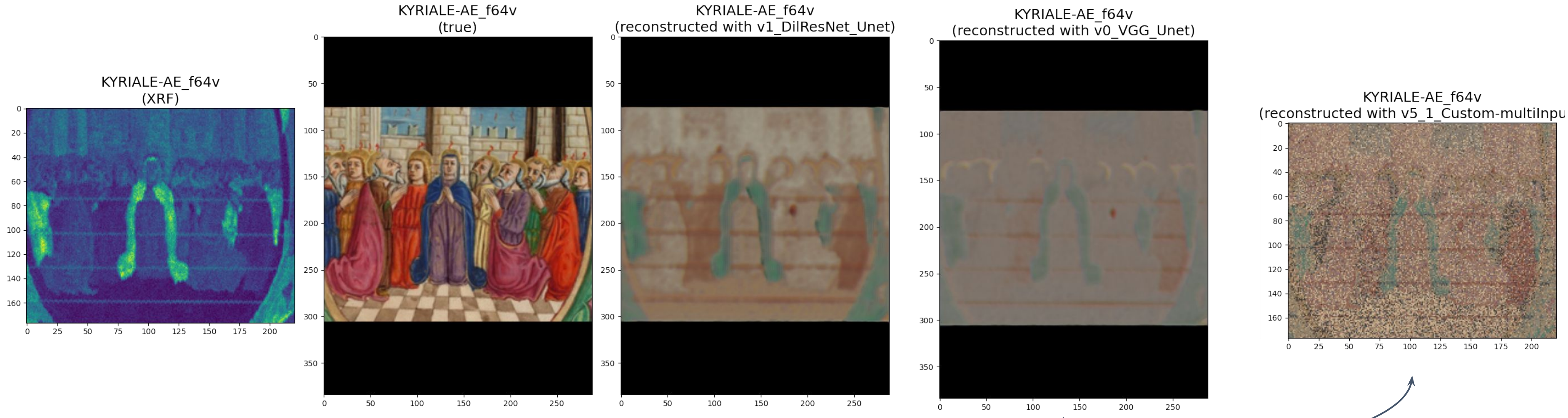
Model parameters: 2179779
Losses: SSIM=0.55; MS-SSIM=0.566; PSNR=18.204; BCE=0.442; MSE=0.015;

GO BACK



2D: Dilated Residual UNet

RESULTS



Model parameters: 2179779
Losses: SSIM=0.55; MS-SSIM=0.566; PSNR=18.204; BCE=0.442; MSE=0.015;

Model parameters: 15246659
Losses: SSIM=0.546; MS-SSIM=0.505; PSNR=17.381; BCE=0.465; MSE=0.018;

Model parameters: 2482731
Losses: SSIM=0.058; MS-SSIM=0.209; PSNR=13.816; BCE=0.767; MSE=0.042;

GO BACK

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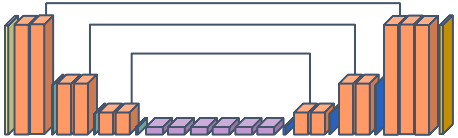
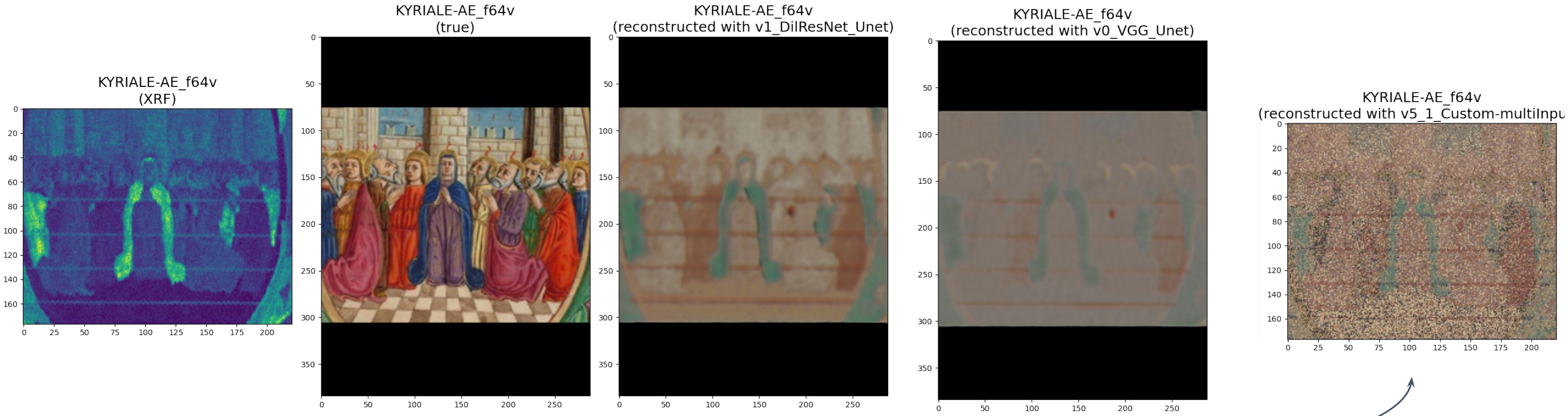


2D: Dilated Residual UNet

RESULTS



Model parameters: 2179779
Losses: SSIM=0.55; $\boxed{\text{MS-SSIM=0.566; PSNR=18.204; BCE=0.442; MSE=0.015;}}$

Model parameters: 15246659
Losses: SSIM=0.546; MS-SSIM=0.505; PSNR=17.381; BCE=0.465; MSE=0.018;

Model parameters: 2482731
Losses: SSIM=0.058; $\boxed{\text{MS-SSIM=0.209; PSNR=13.816; BCE=0.767; MSE=0.042;}}$

Here 2D outperforms 1D!

GO BACK

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AIRES-CH

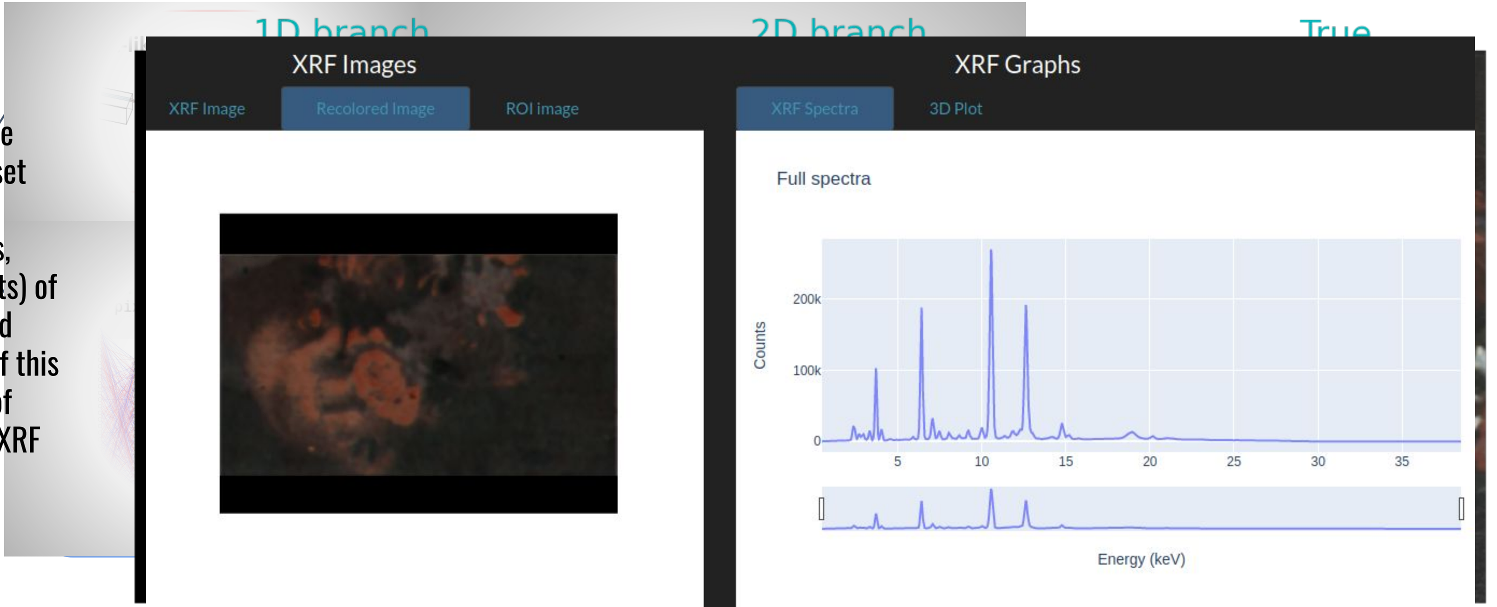
Conclusions

Analysis of Results

Artificial Intelligence for digital REStoration of Cultural Heritage (AIRES-CH) aims at building a web-based app for the digital restoration of pictorial artworks through Computer Vision technologies applied to physical imaging raw data.

The goal is to develop a DNN capable of inferring the RGB image from an XRF image (i.e. the 3D tensor [h,w,E]); this will be obtained by a multi-dimensional DNN, capable of exploiting features of 1D and 2D DNN.

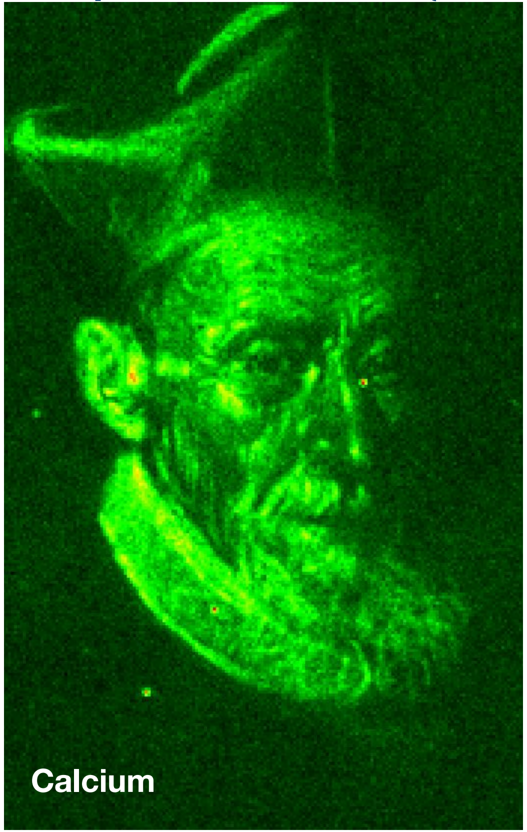
Up to now, the two branches were developed and trained on a dataset formed by XRF images of various pictorial artworks (e.g. paintings, drawings, illuminated manuscripts) of different geographical origins and historical periods, and the goal of this project is to show that the goal of inferring an RGB image from an XRF image is feasible.



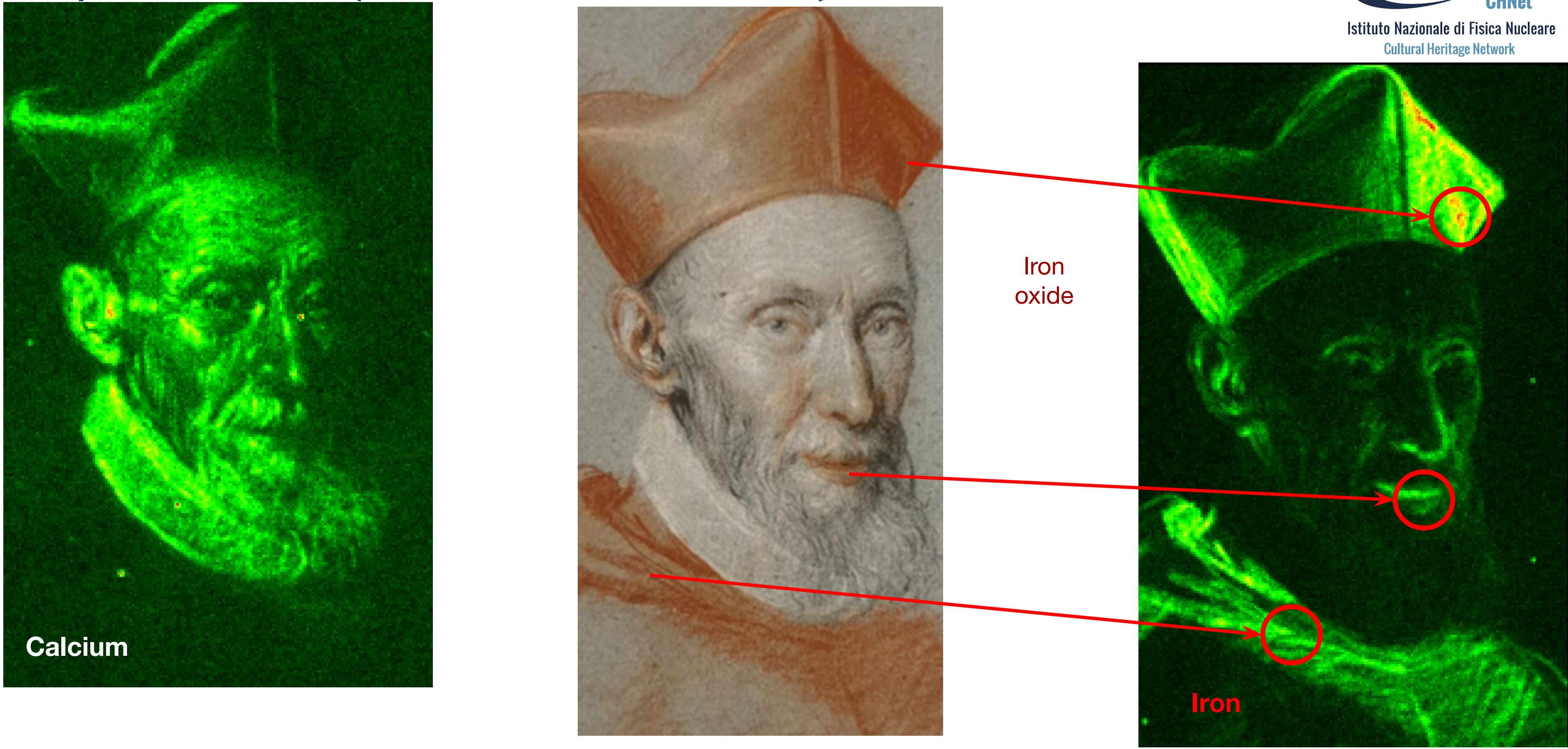
The DNN is furnished in alpha version in the XRF web app.

- Learns from raw images pixels' histograms
- Learns how to associate RGB to peaks distributions
- Learns spatial correlations
- The refiner networks learns how to properly merge the two

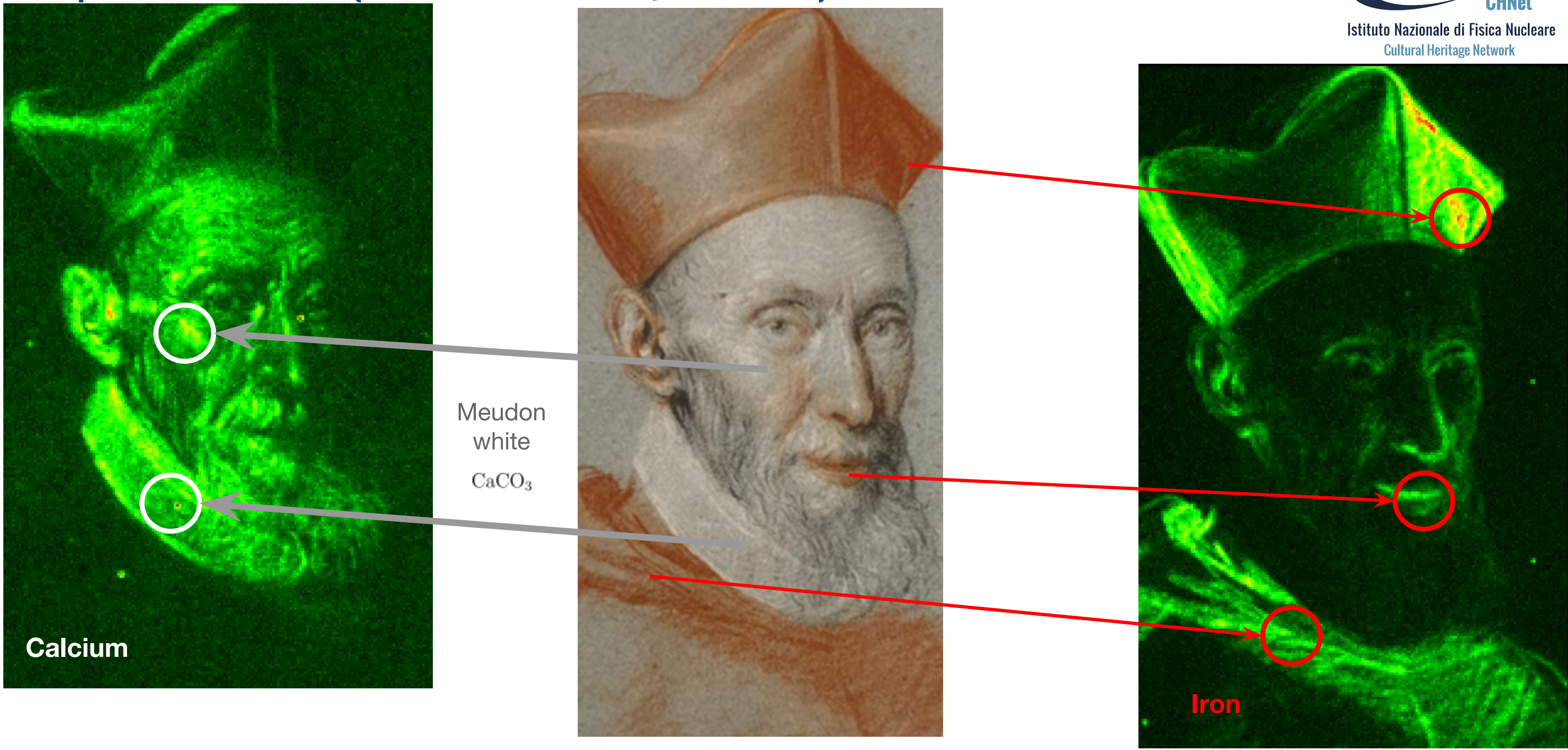
Example: Ottavio Leoni (late XVII sec. - early XVIII sec.)



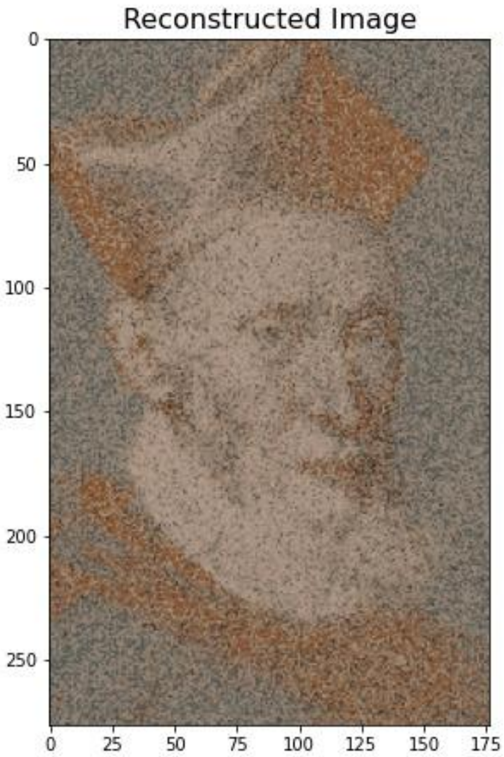
Example: Ottavio Leoni (late XVII sec. - early XVIII sec.)



Example: Ottavio Leoni (late XVII sec. - early XVIII sec.)



Example: Ottavio Leoni (late XVII sec. - early XVIII sec.)



Ottavio Leoni, "Cardinale Antonio Maria Sauli", 1621.
by courtesy of Accademia "La Colombaria"

Another example: Van der Weyden

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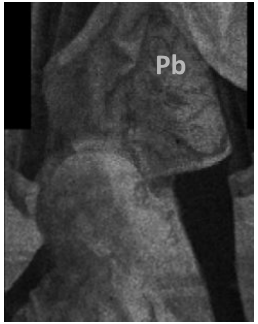
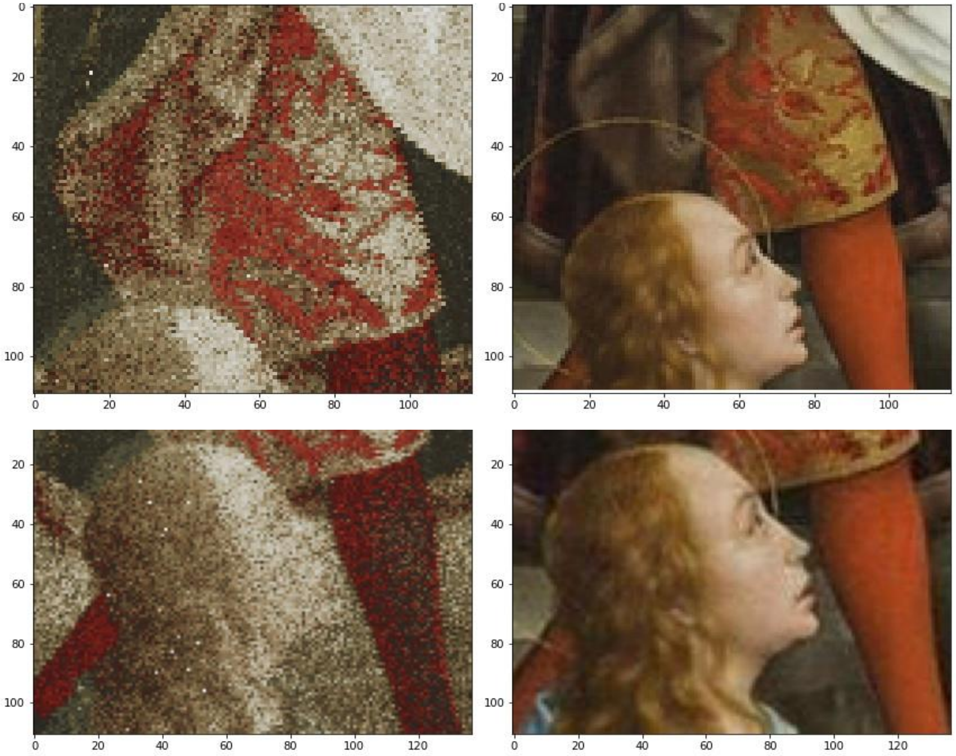
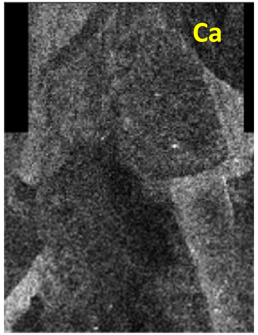
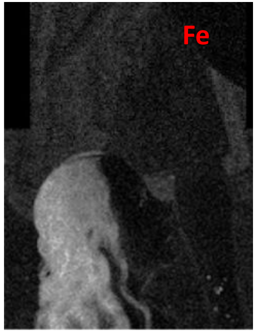






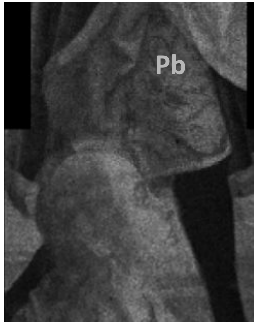


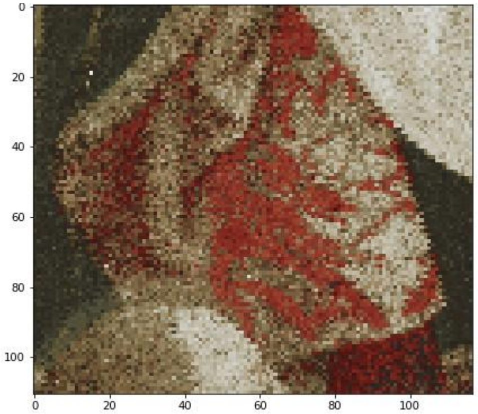
Van der Weyden, “Lamentation of Christ”, 1460
by courtesy of Galleria degli Uffizi

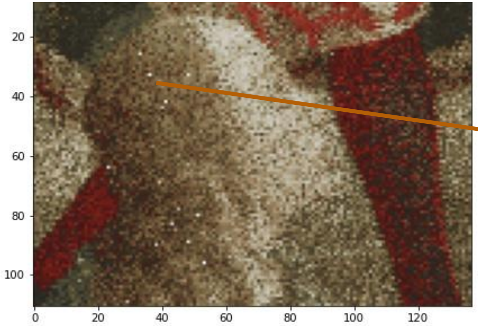
Another example: Van der Weyden

Van der Weyden, "Lamentation of Christ", 1460
by courtesy of Galleria degli Uffizi

Another example: Van der Weyden







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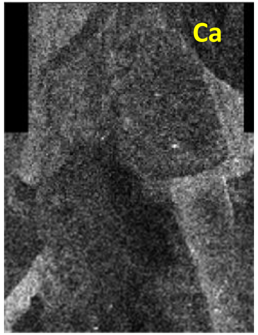

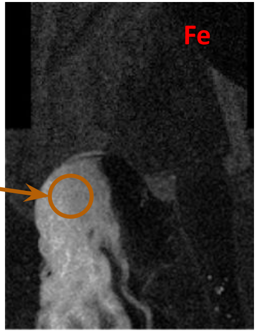

Van der Weyden, “Lamentation of Christ”, 1460
by courtesy of Galleria degli Uffizi

THE END

Alessandro Bombini
email: bombini@fi.infn.it

COMPETENCE CENTRE FOR THE CONSERVATION OF CULTURAL HERITAGE

Coordination and Harmonisation of National &Thematic Initiatives to support EOSC

Regione Toscana