Research Progress Report:

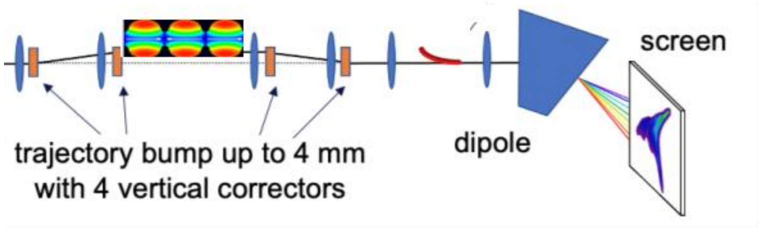
Implementation of Machine Learning in Virtual Diagnostics for Longitudinal Phase Space Reconstruction in High-Energy Accelerators

Daresbury, 3rd September 2026

BACKGROUND

Background:

- Measuring the longitudinal phase space (LPS) using conventional techniques is often invasive and destructive, as the beam must be intercepted to obtain the required measurements.
- LPS properties can alternatively be inferred using non-invasive diagnostics combined with computer simulations. However, detailed particle tracking is computationally expensive and time-consuming. **This research therefore aims to develop machine-learning-based virtual diagnostics** that use non-invasive measurements and machine parameters to rapidly predict the longitudinal beam properties, enabling faster and more practical accelerator diagnostics.

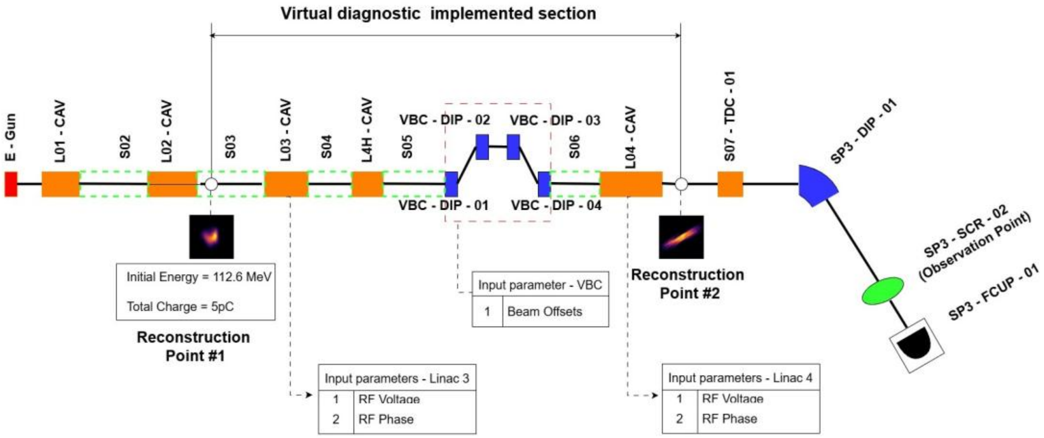


Research Objective:

To develop machine-learning models that use non-invasive diagnostic data and machine parameters to rapidly reconstruct and characterise the longitudinal beam phase space.

TRAINING DATA

- **Implementation of Virtual Beam Diagnostics:**



- **Generation of Training Data:**

1. Fixed Initial Beam Distribution at the RP#1

- Use a constant initial 6D particle distribution for all simulations.

2. Vary Machine Parameters

- Linac 3 RF voltage and phase
- Linac 4 RF voltage and phase
- Beam offset / VBC offset

3. Cheetah Particle Tracking

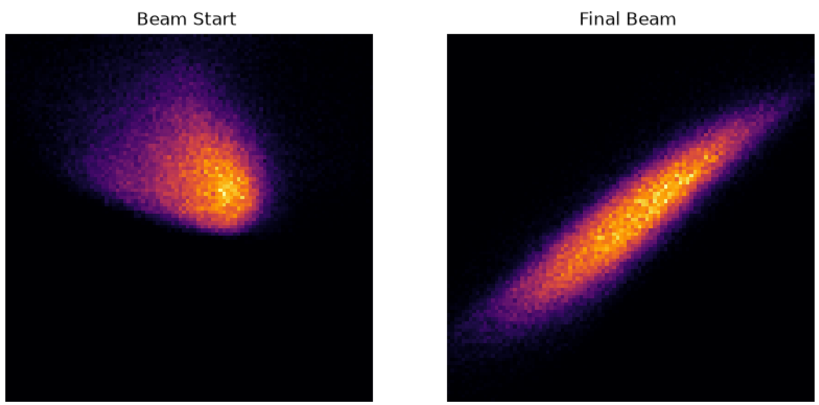
- Update the CLARA lattice according to each machine setting.
- Track the same initial beam distribution through the lattice from RP#1 to RP#2.

TRAINING DATA

- Number of Training Data: 3000
- Constant Initial Beam Distribution

- Training Data consisting of:

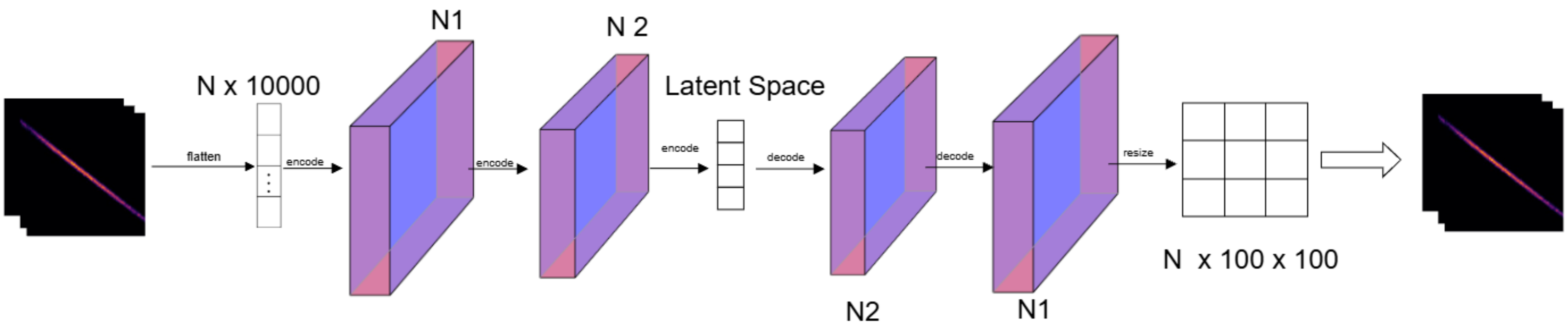
1. Five machine parameters, each standardised using its corresponding mean and standard deviation.
2. Longitudinal phase-space images with a resolution of 100 × 100 pixels in normalized coordinates;



Input parameters		Nominal value	Range
Bunch compressor	Beam offsets (mm)	225	150 - 300
Lin-03-CAV	RF voltage (MV)	85.3	± 10 %
	RF phase (deg)	20.0	± 35 degree
Lin-04-CAV	RF voltage (MV)	57.3	± 10 %
	RF phase (deg)	0.0	± 35 degree

1. Build an autoencoder

- Since the input consists of only five machine parameters, it has a relatively low dimensionality, whereas the virtual diagnostic output is a 100 × 100-pixel image.
- Therefore, directly mapping the input to the high-dimensional output using a standard neural network is challenging.
- An autoencoder is used to extract the main features and reduce the dimensionality of the output before reconstruction.



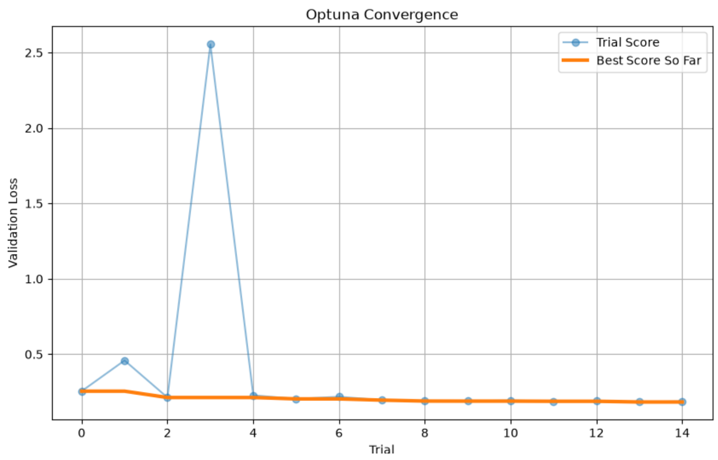
Encoder:
1. Linear Layer 1: 10000 → N1
2. Activation Function #1
3. Linear Layer 2: N1 → N2
4. Activation Function #2
5. Linear Layer 3: N2 → Latent_dim
6. Activation Function #3

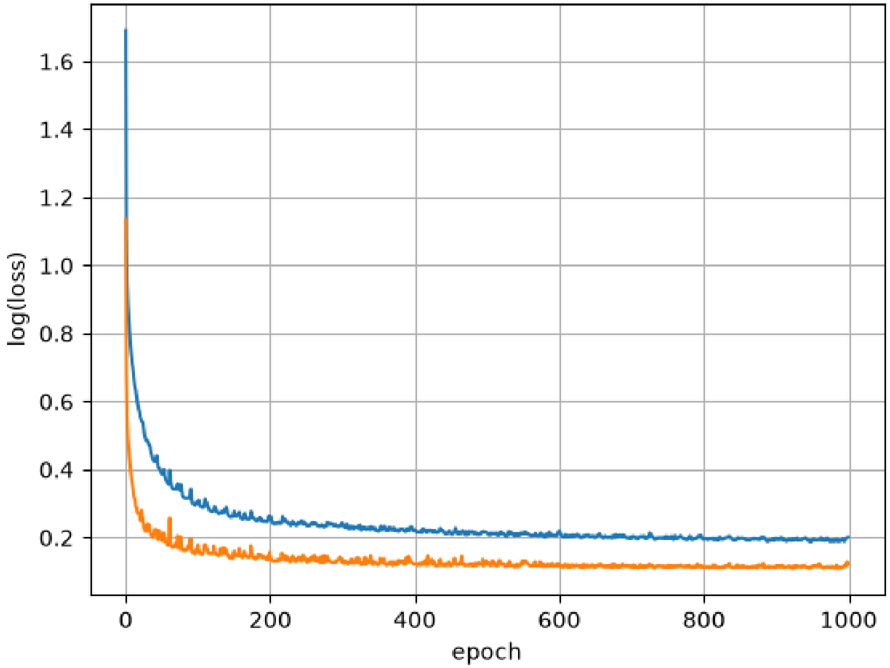
Decoder:
1. Linear Layer 3: Latent_dim → N2
2. Activation Function #3
3. Linear Layer 2: N2 → N1
4. Activation Function #2
5. Linear Layer 1: N1 → 10000
6. Activation Function #1

Loss function: MSE (Mean Squared Error)

1. Build an autoencoder

Result of optimization parameters using Optuna :
Latent space dimension: 27
Hidden1 (N1): 776
Hidden2 (N2): 564
Activation function: leaky_relu
learning_rate: 0.00015027416052902957
optimizer: AdamW



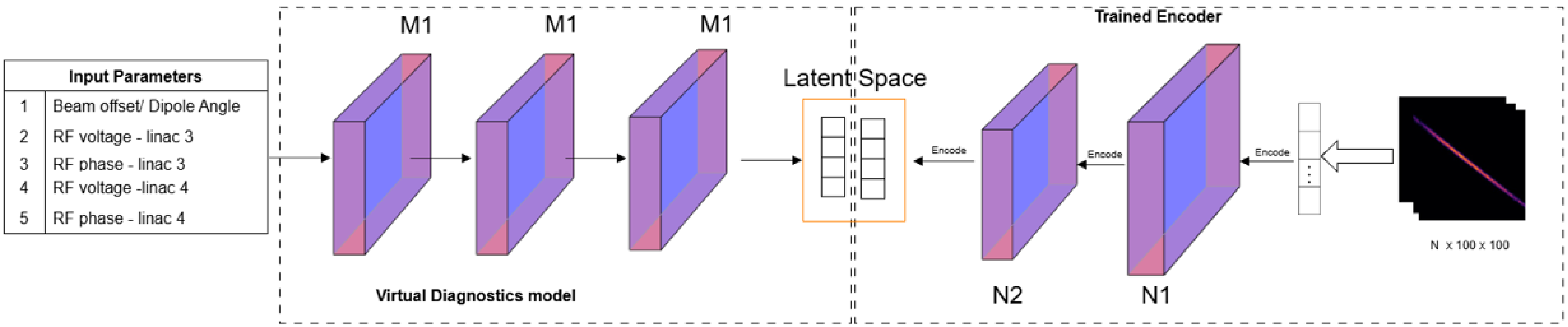


Training dataset: 90%
Validation dataset: 10%

BUILD VD MODELS

2. Build the second neural network model: the Virtual Diagnostics Model

- The virtual diagnostics model is designed to provide a function that maps the machine parameters to the latent-space representation.
- The latent-space parameters are obtained using the trained encoder of the autoencoder, with the corresponding longitudinal phase-space images as input.



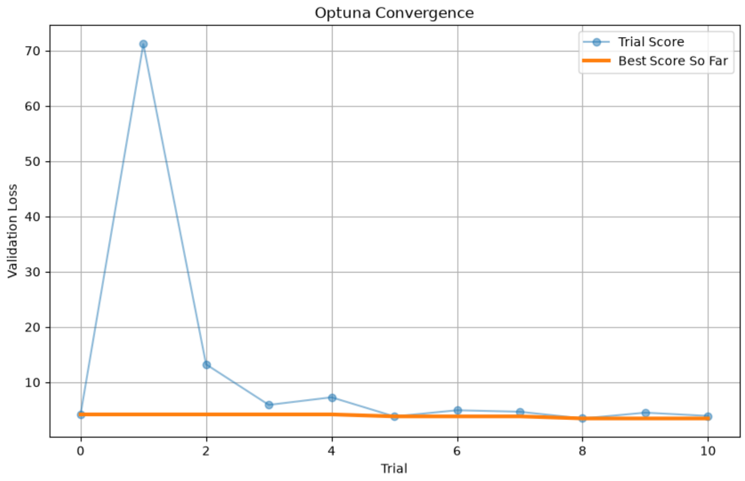
The model consists of **four fully connected (linear) layers**, with an activation function after each layer:

1. Linear Layer 1: Input_parameters → M2
2. Activation Function #1
3. Linear Layer 2: M2 → M2
4. Activation Function #2
5. Linear Layer 3: M2 → M2
6. Activation Function #3
7. Linear Layer 4: M2 → Latent_dim
8. Activation Function #4

Loss function: MSE (Mean Squared Error)

2. Build the second neural network model: the Virtual Diagnostics Model

Result of optimization parameters using Optuna :
Node Number M2: 58
activation: ELU
learning_rate: 0.0029737660434294927
optimizer: AdamW



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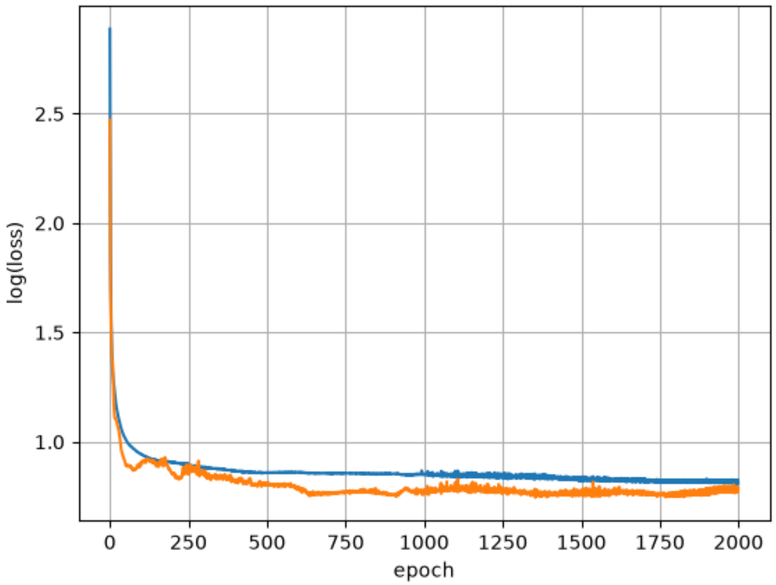
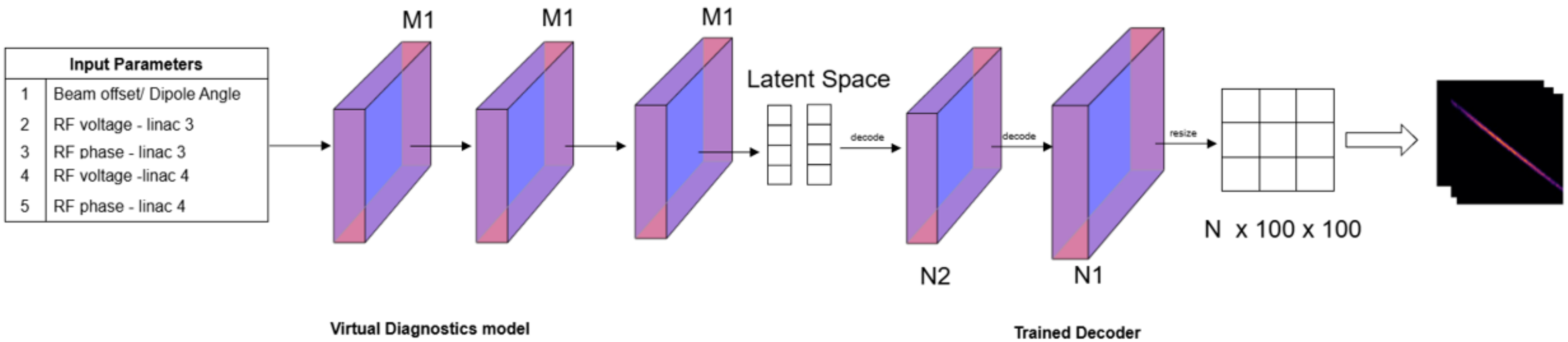
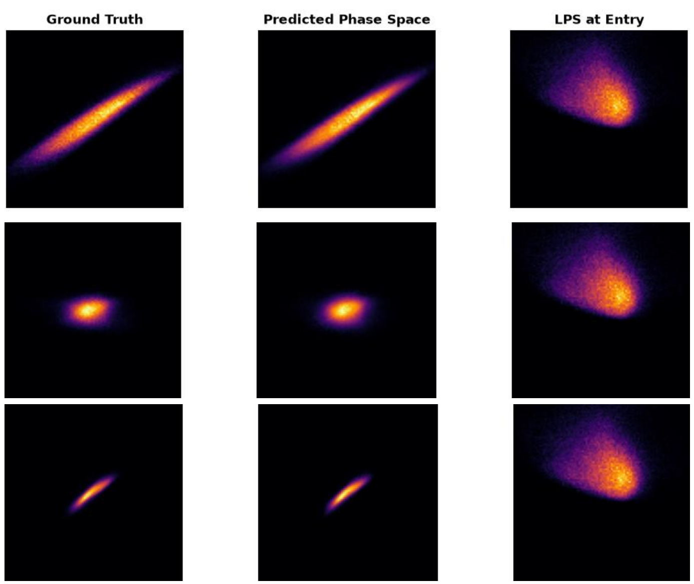
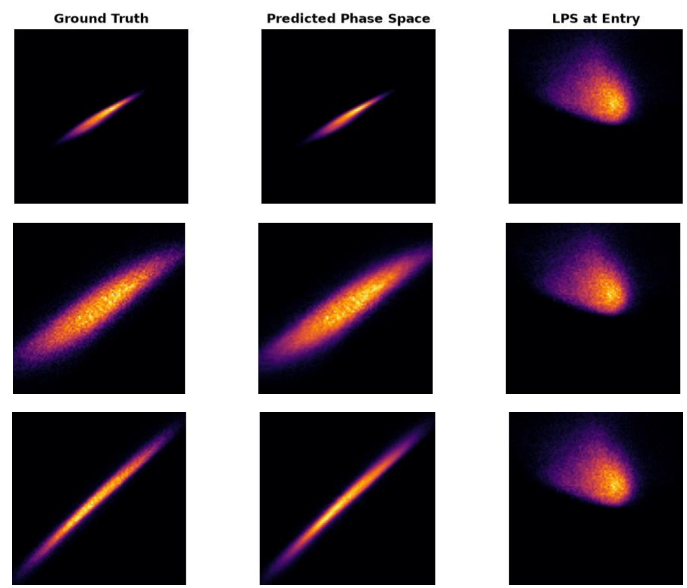


EVALUATION

- In the reconstruction process, the Virtual Diagnostics (VD) model maps the machine parameters to the corresponding latent-space representation.
- The trained decoder then uses these latent-space parameters to reconstruct the longitudinal phase-space distribution.







Thank You

Q & A