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MILESTONE REPORT

ML-BASED CLASSIFICATION AND EVALUATION OF THE BEAM PROFILE PATTERNS

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Abstract:

Beam quality is the most important parameter in the operation of the IRRAD facility at CERN. A dedicated Beam Profile Monitor (BPM) sensor was developed and recently significantly improved thanks to a new manufacturing technology based on microfabrication of metal nano-layers.

In particular, the new BPM sensor features higher sensitivity, minimal particle interaction and an improved radiation hardness. Today, to be able to exploit all features of these new BPM sensors, the DAQ technology and the handling of the BPM data can also to be substantially improved with the innovative idea of applying Machine Learning (ML) techniques. This report details the first prototype of an ML model aiming to perform the automatic pattern recognition or anomaly detection of beam profiles. The performance of this new ML model is tested in this report using beam data taken during the run of IRRAD in 2024.

For more information on EURO-LABS, its partners and contributors please see https://web.infn.it/EURO-LABS/

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Executive summary:

New Beam Profile Monitor (BPM) sensors developed for the IRRAD facility at CERN feature higher sensitivity, minimal particle interaction and an improved radiation hardness. To be able to exploit all features of these new BPM sensors, the DAQ technology and the handling of the BPM data are foreseen to be substantially improved by applying the innovative idea of Machine Learning (ML) techniques. This report details the first prototype of a ML model aiming to perform automatic pattern recognition or anomaly detection of beam profiles. In this report, performance of this ML model is tested using beam data taken during the run of IRRAD in 2024.

1. INTRODUCTION

The IRRAD facility is located in the T8 beamline of the East experimental Area at CERN (Fig. 1 – left-hand side). For its operation, IRRAD exploits the 24 GeV/c proton beam extracted from the Proton Synchrotron (PS) ring. The IRRAD beam requires constant beam quality monitoring, therefore, along the beamline, four Beam Profile Monitor (BPM) sensors are placed to provide constant and real-time monitoring of the transverse beam profile that is Gaussian and has a nominal size of 12×12 mm^2 FWHM (full width at half maximum) [1]. This information, available on dedicated webpages[1], is used by the beam operation team to steer the irradiation beam as well as by the IRRAD users to analyse the data of their irradiation experiments (Fig. 1 – right-hand side). The BPM sensors, based on the Secondary Electron Emission effect [2] feature a matrix of pixelated metal pads of about 4×4 mm^2 (40 channels) connected to a Data Acquisition (DAQ) system upgraded in the framework of the EURO-LABS project [3]. Every DAQ unit supports up to 160 channels to acquire data from four BPMs in parallel.

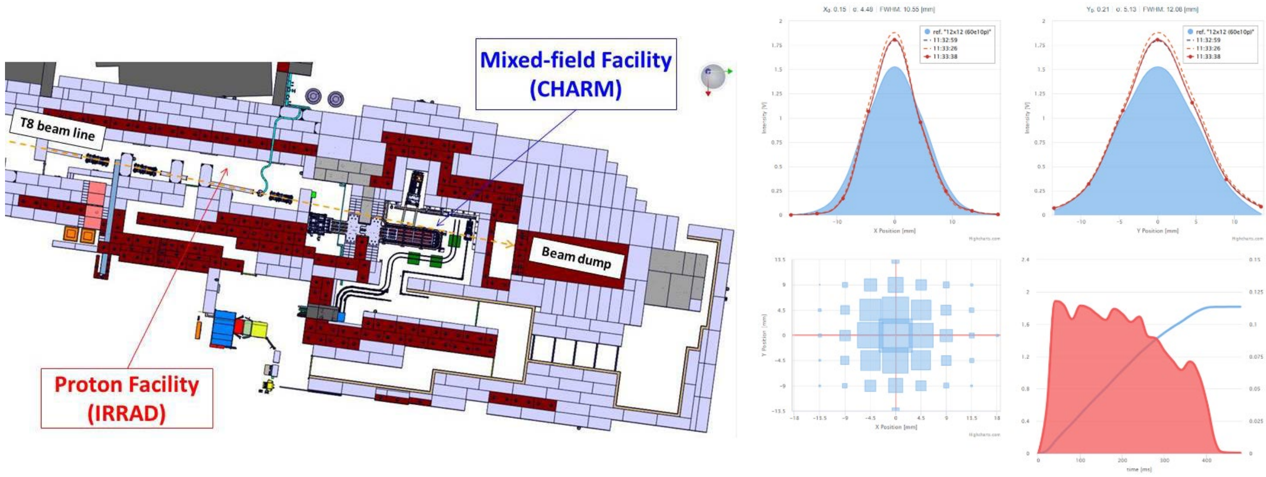

Figure 1 - The location of the IRRAD Facility within the CERN East Area (left-hand side), and the Gaussian profile of the 24 GeV/c proton beam as measured by the IRRAD BPMs (right-hand side).

This unique setup provides a constant data volume of about 480 samples/s for every single BPM. That results in the data flow of raw measurements reaching about 160 MB/day. This data opens a possibility towards an intelligent analysis of IRRAD beam profiles and to define new metrics for beam characterization.

[1] https://op-webtools.web.cern.ch/irrad/#/

In the framework of the EURO-LABS project, we developed and describe here the usage of Machine Learning (ML) models and algorithms in the BPM data processing pipeline to study possible improvements in the efficiency and precision of the beam profile monitoring.

2. DATA MODEL DEFINITION

2.1. DATA ACQUISITION

To monitor the beam profile, the BPM sensor with 40 channels is connected to the upgraded DAQ system [3]. The new readout electronics measures the currents in the 1-100 nA range and provides a sampling rate of up to 1 kHz that allows signal processing from four BPMs in parallel, totalling in 160 channels per DAQ unit. The resulting dataflow reaches 480 samples/s for every single BPM, yielding a total data volume of about 160 MB/day.

These data are used to build a dataset that allows ML models to be trained towards automatic pattern recognition or anomaly detection of beam profiles. Due to the BPM pixelized pattern of pads, each single profile measurement may be easily treated as an image (Fig. 2). This approach allows to use the processing techniques known from computer vision such as Convolutional Neural Network (CNN) based techniques, that are very well known for its versatile and efficient applications [4]-[5].

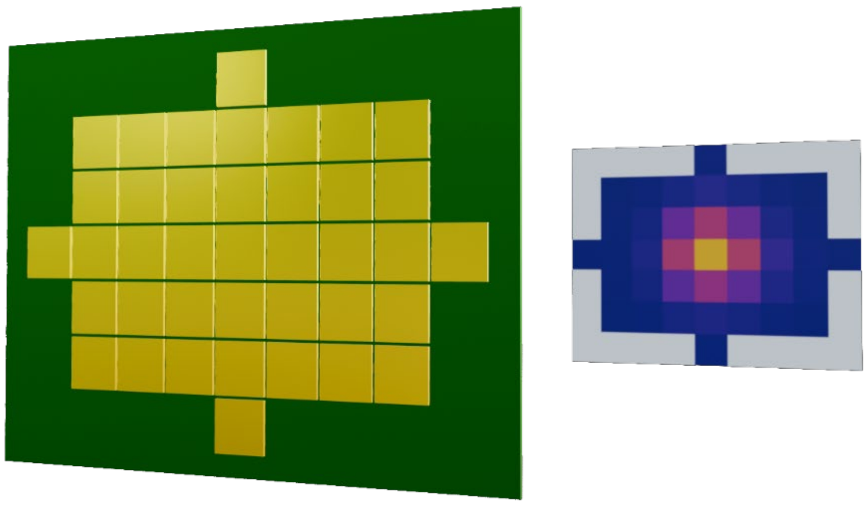

Figure 2 - The model of the BPM sensor printed circuit board (PCB) on the left-hand side, confronted with the measurement data presented in the form of the image (right-hand side). With such representation, it is possible to use image processing techniques such as Convolutional Neural Networks (CNN) and develop models capable of beam classification.

2.2. DATASET OF BEAM PROFILES

The dataset is composed of images representing the centred- and off-centred beam profiles (Fig. 3). Currently, the dataset presented in this Milestone report consists of around 6,700 images of desirable, good-quality beam profiles (e.g. aligned on the central BPM pad) and more than 2,000 examples of off-centred beam.

The data was first numerically analysed. Data from each BPM record was used to construct its Gaussian fit. Based on the values of calculated properties, such as beam centre coordinates, amplitude, and fitting errors, the character of each beam profile was determined.

The samples are clearly imbalanced due to the nature of operational beam quality that stays within acceptable ranges for most of the time. Nevertheless, with a specific selection of models this aspect can be easily mitigated. Aiming for anomaly detection (triggering alerts when beam becomes off-centre) or one-class pattern classification, the good quality profiles are needed for model training and the others only to verify the accuracy of computer results.

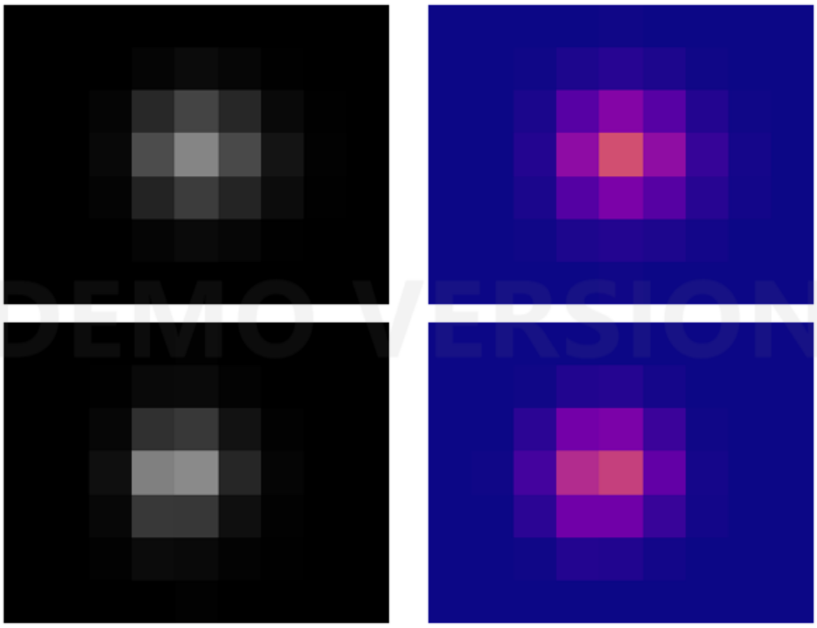

Figure 3 - The examples of BPM recorded data are visualized in the form of low-resolution images when each pixel and its greyscale brightness correspond to the value measured with individual pads (left-hand side). To provide even better visualisation, a colour-map may be assigned (right-hand side). In the top half of the figure, the example shows a well-centred beam profile, while at the bottom an off-centred beam can be observed.

3. MACHINE LEARNING FOR BEAM PROFILE CLASSIFICATION

3.1. CONVOLUTIONAL AUTOENCODER

Considering the character of the available data, the decision to pursue the case study of a Convolutional Autoencoder (CAE) [6] was made.

In general, the Autoencoder is a type of artificial neural network that learns the efficient coding for presented data, therefore it falls in the category of *unsupervised learning* – a specific process where the training relies on unlabelled image data. This coding is reversible; therefore, this type of neural network can reconstruct the original data from its latent representation.

The CAE is a specific type of autoencoder that processes images with convolutional layers known from Convolutional Neural Networks (CNN). It is capable of learning patterns and specific features that are present in the given images. For the learned features, the image reconstruction is possible as well. However, an accurate result will be obtained only for the specific classes of images that were available in the training dataset.

3.2. ANOMALY DETECTION WITH AUTOENCODER NEURAL ARCHITECTURE

The autoencoder's ability to perform original sample reconstruction through encoding into a compressed representation (latent representation) and then decoding it back is the mechanism that makes tasks such as anomaly detection and one-class classification possible.

If the training dataset content is adjusted to consist only of good-quality beam profiles (the images of the well-centred beam), the neural architecture will learn towards a perfect reconstruction of the presented sample (Fig. 4.).

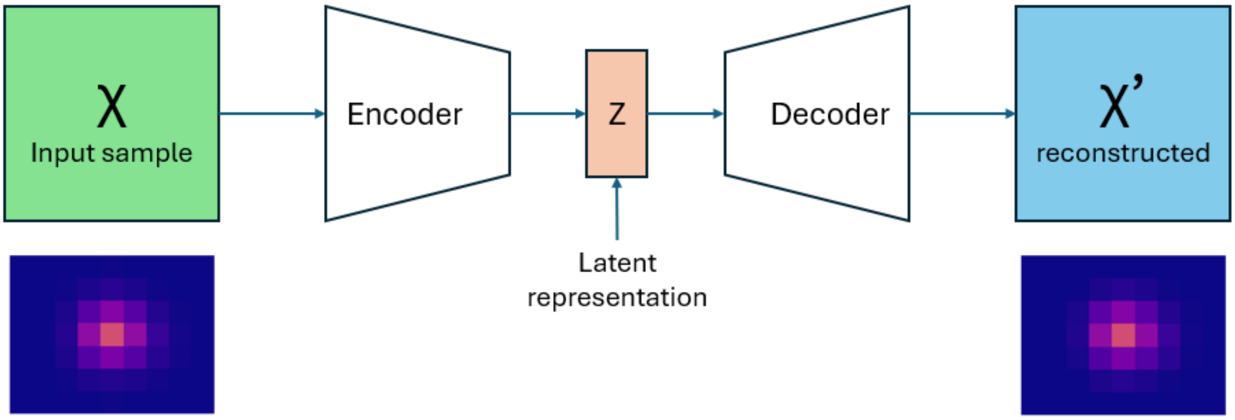

Figure 4 - The Convolutional Autoencoder (CAE) is a type of Convolutional Neural Network that is able to create a compressed representation of the input sample and then reconstruct it. Ideally the reconstructed image is identical to the original. If the learning process involves usage of a specific class of images, the CAE may be used in one-class classification or anomaly detection.

However, such reconstruction will only be possible for the samples similar to those presented during the training process. The reconstruction shall fail for the images with unknown characteristics and patterns. This feature is to be explored for the creation of automatic assessment of beam profiles.

3.3. IMAGE SIMILARITY METRICS

To perform proper training of the ML-based model, the proper loss function and performance metrics are to be defined and verified.

Such metrics as Mean Square Error (MSE) or Mean Absolute Error (MAE) are used to calculate the difference between target and predicted values between given pairs of vectors, matrices or multidimensional tensors. Yet, there are metrics directly envisioned for image processing, thus suited much better to be applied for the convolutional autoencoder:

- Peak signal-to-noise ratio (PSNR) describes the ratio between the maximum power of the signal and the power of corrupting noise that affects the fidelity of the representation; hence it is used to measure the reconstruction quality of a given image. It is usually used to quantify and assess the reconstruction quality of images when applying lossy compression.
  The original data in our case is based on 40 BPM channels which are treated as images with matrices of 7×9 pads (see Figure 3). PSNR value for such small resolution may change

drastically even if overall reconstruction is close to original. Additionally, since PSNR is taking into account only pixel-wise difference between the original and reconstructed image, a more precise metric is needed for this task.

- Structural Similarity Index Measure (SSIM) is a perception-based measure designed to capture the change in structural information, luminance and contrast [7]. It compares the local patterns of pixel intensities; and these features make it a good metric to use in the beam quality assessment with the presented BPM data. Metric values are within range $\in \langle 0.0, 1.0 \rangle$, (0.0) indicating bad and (1.0) perfect reconstruction or quality.

This analysis selected for the prototype presented here leans towards the usage of the SSIM metric in this particular case.

4. IMPLEMENTATION

4.1. EXPERIMENTAL SETUP

The final machine learning model is built as the described CAE model. The details of its architecture are presented in Table 1.

The CAE consist mostly of 2D Convolutional and Pooling layers in the encoder and (de)Convolutional and Up-sampling layers in the decoder. This allows the model to learn high-level features of each image and later use them to reconstruct the sample.

Table 1 - The detailed specification of CAE layers. First, the convolutional and pooling layers are used to construct a compressed, latent representation of the image of the BPM profile in the encoder part. Then this process is reversed to reconstruct the image. The original image is resized due to more convenient handling of a square-like object. However, as the resizing layer can be a part of the neural model, its weights are also learned during the training process.

Encoder layers	Decoder layers

`Input(7,9)`
`Resizing(16, 16)`
 	
`Conv2D(64, (3, 3))`
`MaxPooling2D((2, 2))`
`Conv2D(16, (3, 3))`
`MaxPooling2D((2, 2))`
`Conv2D(8, (3, 3))`
`MaxPooling2D((2, 2))`
	`Conv2D(8, (3, 3))`
	`UpSampling2D((2, 2))`
	`Conv2D(16, (3, 3))`
	`UpSampling2D((2, 2))`
	`Conv2D(64, (3, 3))`
	`UpSampling2D((2, 2))`
	`Conv2D(1, (3, 3))`
	
	`Resizing(7,9)`
	`Output(7,9)`

As the CAE is a basis for the final solution, it is followed by the Structural Similarity Index Measure calculation. That result is then assessed in the discriminator block: based on an experimentally established threshold, the final assessment is made (Fig. 5).

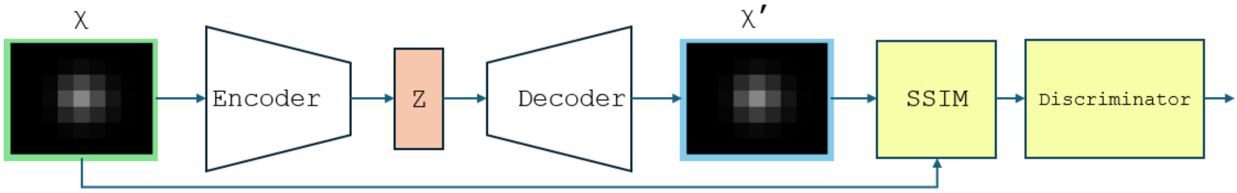

Figure 5 The architecture of anomaly detection solution. Both the input image and reconstructed image are used to calculate the similarity metric. Then the discriminator calculates the decision based on the metric value.

4.2. TEST SCENARIO AND NUMERICAL RESULTS

The experiments were run in the SWAN (Service for Web based ANalysis) environment - a Jupyter Notebook-based solution developed at CERN and in the Saturn Cloud web platform. The assigned machine setup involved 4 cores CPU, 32GB of RAM and an NVIDIA TESLA T4 GPU.

4.2.1. Model Training

The training process involved the mentioned beam profile dataset that was divided into *training : validation : test* subset with respective ratios of 0.70 : 0.15 : 0.15. This approach is a standard technique to split the data used for training from the one used for model verification. Such an assessment is more objectively verifying the data as the validation step does not use the data that was seen during the training step.

With the decision to use SSIM as a metric during the training (where values > 0.90 mean high quality of the reconstruction process), the loss between the reconstructed $\hat{y}$ and original sample y is defined as follows:

$$Loss(\hat{y}, y) = 1 - SSIM(\hat{y}, y)$$

Table 2 - The value of loss function during the autoencoder training process.

Subset	Loss value
Training	0.0084
Validation	0.0046

As presented in Table 2, the minimized value of the loss function reached a satisfactory value. In this case, it indicates that with the training and validation data, the SSIM metric was reaching well over 0.90 – so the quality of reconstruction is very satisfactory.

4.2.2. Model Evaluation with Real Data

To finalize the assessment, the threshold for the discriminator block was adjusted with the test subset of the data. The mean value of the SSIM metric achieved on this subset was chosen:

$$Threshold = \lfloor MEAN(SSIM_{Test}) \rfloor = 0.93$$

Every time the SSIM between the original and reconstructed sample exceeds this value, it is assessed to be a well-centred beam profile.

The real data was used to verify the usefulness of the model. As the IRRAD facility constantly monitors the beam during operation, the data of "Week 20" was selected to verify if the results of numerical analysis and the machine learning solution will be coherent. This set contains 40,351 samples of beam profiles for evaluation.

"Week 20" was a very specific week of balanced *centred / off-centred* beam representation:

- The beam was centred in the x-axis ($\pm 2mm$) 56.7% of the time.
- The beam was centred in the y-axis ($\pm 2mm$) 94.5% of the time.
- The beam remained in the strict centre of x-y plane 54.2% of the time.

The assessment performed with a custom CAE model yielded the result of **51.0%** of correctly centred beam profiles. While there is a slight difference between this result and numerical analysis, there is one factor that is also important – model complexity and its execution time.

The evaluation of the selected 40,351 samples took on average:

- 526.6 seconds for the numerical solution based on Gaussian Fitting (76 samples/s).
- 32.3 seconds for the solution based on Convolutional Autoencoder (1249 samples/s).

The Machine Learning based computations took over 16 times less time than the analytical solution. This is an important step towards ensuring a real-time regime of Beam Profile Monitoring.

5. SUMMARY AND FUTURE WORK

5.1. SUMMARY

In the framework of the EURO-LABS project, we presented the result of research work within Milestone 29 *"ML-based classification and evaluation of the beam profile patterns*". The evaluation study is based on a Convolutional Autoencoder, and it achieves satisfactory and accurate results. Moreover, the processing efficiency of the proposed model allows to consider its usage in the real-time regime. These are the crucial factors for a beam monitoring system in any irradiation facility.

5.2. FUTURE WORK

The project focused on using Machine Learning models in the evaluation of beam profiles is promising and thus worth continuing.

As the evaluation study was presented solely as a prototype of such a solution, using a programming framework for Machine Learning, and not solutions optimized for any kind of hardware, it is possible that an optimized solution can be much faster and more accurate.

Additionally, more sophisticated solutions can be envisioned with novel neural architectures such as Transformer models with attention mechanisms [8]. This development can allow the processing of not only single profiles but also a time series of beam profiles.

A reliable space-time characterization of the proton beam can be achieved with the novel BPM electronics and properly engineered Machine Learning software; therefore, it is the future research direction to be pursued.

6. REFERENCES

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ANNEX: GLOSSARY

Acronym	Definition
BPM	Beam Profile Monitor
CAE	Convolutional Autoencoder
CNN	Convolutional Neural Network
DAQ	Data AcQuisition system
IRRAD	CERN Proton IRRADiation Facility