AI Tools for Plasma Diagnostics by X-ray Imaging and Spectroscopy in the PANDORA Project Frame

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Abstract

Magnetized plasmas in compact traps offer a unique environment for fundamental research. PANDORA is a multidisciplinary project focused on studying β decays in plasmas, using a novel facility that replicates stellar-like conditions—marking a significant advance for probing weak interactions in astrophysical scenarios. The project also supports applications to materials science, accelerator and ion source technologies, etc. A diagnostics system is based on a soft X-ray pinhole camera has been designed and implemented, with its own innovative algorithm for Single-Photon Counting analysis. This enables space-resolved plasma spectroscopy and the determination of magneto-plasma properties like local thermodynamic parameters and confinement dynamics. This work presents results from an AI-based model in MATLAB designed to optimize that algorithm. Using *K-means* clustering, events with similar features were grouped to identify those distinguishing real from spurious ones. A labeled dataset then is used to train a neural network to minimize pile-up, accelerating the recovery of high-resolution spectra and improving soft X-ray emission analysis. This contribution presents the the current neural network development stage and first applications to experimental data.

Introduction

The PANDORA project, under development at INFN-LNS in Catania, aims to study in-plasma β-decays of key radioisotopes for nuclear astrophysics using an ECR plasma trap that mimics stellar-like conditions. [1] The same setup also allows investigation of plasma optical properties and astrophysical scenarios relevant to multimessenger astronomy, such as opacity. [2] Plasmas naturally emit across the electromagnetic spectrum. To fully characterize this emission, PANDORA will implement an extensive diagnostic system [3]. Our focus lies on the soft X-ray range (0.5–30 keV), associated with warm electrons that play a key role in ionization processes and charge state distribution within the plasma [1,4].

Experimental set-up and Single Photon Counting Algorithm

The experimental setup includes a CCD camera (Sophia by Princeton Instruments), optimized for soft X-rays, coupled to a lead pinhole aligned with the plasma trap [4]. This configuration enables both spatially and spectrally resolved spectroscopy (our system has been upgraded to get 500 µm and 242 eV @ 8.15 keV resolution [5]). A shuttering system was added to allow time-resolved measurements (with ms resolution). To analyze the acquired data, we developed a Single Photon Counting (SPhC) algorithm, capable of decoupling the photons from their energies based on charge deposition patterns across thousands of fast exposures (5–500 ms) CCD images, thus minimizing photon pile-up probability [4, 5]. Despite the SPhC algorithm has well performed, we are now exploring a machine learning (ML) approach to: 1) enhance the energy resolution and signal-to-noise ratio by further reducing pile-up; 2) enable real-time analysis and potentially identify hidden plasma patterns.

Hybrid Approach and Model Development

In this work, we adopt a hybrid approach that combines the efficiency of an advanced imaging tool—developed within the SPhC algorithm—with both unsupervised (*k-means*) and supervised (*neural network*) machine learning models. The workflow of the data analysis is presented in the following.

1. Features Extraction via Imaging Tool

The first step relies on an imaging tool provided by MATLAB, *bwconncomp*.[6] This connectivity-based function detects events on the CCD matrix and extracts geometric and intensity-related features to build a structured dataset [4,5]. Among these, we focus on three main parameters: *cluster size* (event area in pixels), *number of local maxima* (to identify multi-photon events), and *eccentricity* (ratio of major to minor axis, characterizing the event shape). These features are selected for their interpretability and relevance to the underlying physics and play a central role in the classification process.

2. Unsupervised Learning: K-Means Clustering

Once the dataset is built, we apply *k-means*, a simple yet effective unsupervised clustering technique, to group events based on their features. This enables identification of two main populations: likely valid physical events and spurious or noise-like ones. The resulting binary clustering provides an initial labeling essential for training the supervised model.

3. Supervised Learning: Neural Network Development

With labeled data, we proceeded to train a feed-forward neural network as a binary classifier. Prior to training, the data was normalized using *mapminmax*[7], scaling all features to the [0,1] range to improve convergence and computational efficiency. *Class balance* was carefully monitored to ensure robust training. The dataset was then randomly shuffled and split into three subsets: training (70%), validation (15%), and test (15%). *Randomization* helps avoid systematic bias during training.

Network Architecture and Training

We use a feed-forward neural network implemented on MATLAB, called *patternnet*.[8] This type of architecture processes data in one single direction without feedback loops, making it well-suited for classification tasks. The structure includes an input layer with neurons matching the number of features, followed by a hidden layer of 10 neurons using a hyperbolic tangent activation to capture non-linear patterns while avoiding overfitting. Finally, the output layer consists of a single neuron with a sigmoid function, returning a probability score for class membership.

Training Performances and First Results

Once all parameters were set, we performed the first training of the neural network, obtaining promising results. The network successfully converged in 128 epochs, as shown in the performance plot of the cross-entropy loss, which steadily decreases with each epoch. This loss function, measuring the divergence between predicted and actual class labels, must be minimized to ensure reliable classification. The model's effectiveness is confirmed by the confusion matrix,[8] which shows a 100% accuracy, consistently maintained across training, validation, and test sets.

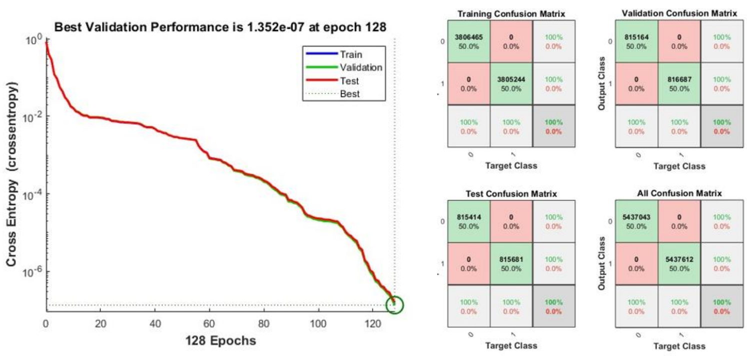

Figure 1. Performance of the net plot featuring the Cross Entropy i.e. the loss function, as a function of the number of Epochs, on the left. Confusion matrices of different training stages, on the right.

Finally, in Fig. 2 we plotted both the spectrum of events correctly classified as valid (green curve), the spectrum of all events before classification (red curve). The resulting spectrum is well-resolved, showing a 2% FWHM at the Krypton peak, demonstrating the network's capability to isolate physically meaningful events.

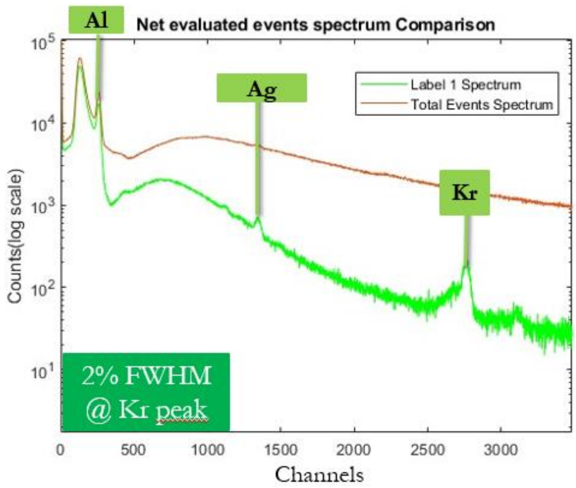

Figure 2. Spectrum of all the events classified as valid by the net, highlighting different, well resolved fluorescence peaks in green, against the plot of all the events in red.

Conclusions

In conclusion, we validated the application of the AI-based unsupervised clustering model to SPhC data recognition of a CCD detector, and developed a feed-forward neural network, obtaining the first labeled event spectrum. However, the network was trained on a single, specific dataset. To improve its performance and generalizability, further training on diverse, unexplored datasets is necessary. The next step is the ongoing Monte Carlo simulation, aimed at generating a synthetic dataset for both additional training and performance evaluation on entirely new data.

References

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