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DEEP NEURAL NETWORK FOR BEAM PROFILE CLASSIFICATION IN SYNCHROTRON

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Abstract

The main goal of National Synchrotron Radiation Centre (NSRC) Solaris is to provide scientific community with high quality synchrotron light. To achieve this, it is necessary to constantly monitor many subsystems responsible for beam stability and to analyze data about the beam itself from various diagnostic beamlines. In this work a deep neural network for transverse beam profile classification is proposed. Main task of the system is to automatically assess and classify transverse beam profiles based solely on the evaluation of the beam image from the Pinhole diagnostic beamline at Solaris. At the present stage, a binary assignment of each profile is performed: stable beam operation or unstable beam operation / no beam. Base model architecture consists of a pre-trained convolutional neural network (CNN) followed by a densely-connected classifier and the system reaches accuracy at the level of 94.10%. The model and the results obtained so far are discussed, along with plans for future development.

INTRODUCTION

Solaris is a third generation light source (shown in Fig. 1) operating at the Jagiellonian University in Kraków, Poland [1]. This advanced and complex scientific infrastructure offers new highly innovative research opportunities for areas including physics, medicine and nanotechnology. Currently at Solaris five experimental beamlines offering various techniques, e.g.: photoemission electron microscopy, X-ray absorption spectroscopy, ultra angle-resolved photoemission spectroscopy or multi-scale X-ray and multimodal imaging, are available to the scientific community whereas another three are already at advanced level of construction and commissioning. Moreover, Solaris is also a National Cryo-EM Centre, with two latest generation cryo-electron microscopes enabling life science researchers to unravel life at the molecular level [2].

Synchrotron control system is large, distributed and controls hundreds of devices and reads measurement and diagnostic data out of thousands. Moreover, due to a complexity of physical phenomena that occurs during the operation i.e. electron injection, beam tuning and beam decay, it is often difficult to quickly determine the reason of beam instabilities or its lost. Manual inspection performed even by an experienced operator is not able to extract full information from hundreds of diagnostic signals, which carry a lot of important information about the state of the machine. The purpose of this work is to present a system that could help operators in detecting potential threats and, in the future, to serve as a tool for predicting anomalies, beam loss or equipment failure.

Figure 1: NSRC Solaris [3].

The use of artificial intelligence (AI) techniques, including machine learning and neural networks, for signal analysis, prediction or anomaly detection has a long history. As the accelerators serve as an interesting research area also here we observe a huge interest in the anomaly detection area where new methods are developed, validated and deployed to solve existing problems regarding the operation of synchrotron radiation systems. Classic neural networks or machine learning frameworks take advantage of archived data of beam position in the storage ring in order to determine the appropriate orbit correction to minimize the proposed cost function [4, 5]. The problem of anomaly detection and failure prediction in the accelerator control systems has also been discussed during the ICALEPCS or IBIC conferences and different approaches has been proposed [6, 7]. Finally, various applications of artificial intelligence based systems has been identified in the fields like beam stabilization, autonomous operation, optimisation and performance improvements [8–10]. Since there is such a high demand on a precise and reliable AI-based systems I propose a deep neural network (DNN) for transverse beam profile classification as a support tool for operators.

BEAM PROFILE CLASSIFICATION SYSTEM

In this section a transverse beam profile classification model based on deep, convolutional neural network is presented. Main idea behind it is to use Pinhole diagnostic beamline beam profiles and employ transfer learning methods to build suited classifier on top of the pre-trained architecture.

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Deep Neural Networks

Deep neural networks have become very popular, resulting in their appearance in many applications and models. It is an attempt to map to some extent the activity of the human brain. Neural networks quickly proved to be effective in solving problems that typical programs or algorithms do not cope with or become too complicated to use. An important feature of the networks is that the they are effective even if the creator of the network himself does not quite know the algorithm that could solve the problem. Only knowledge of the problem and the appropriate selection of parameters and architecture are required. This greatly expands the possibilities of using such models for practical cases. The neural networks after proper training are able to learn a certain process and detect a moment of anomaly or deviation from the norm. The key to success in this case is having sufficiently large retrospective data that can be used to show examples of relationships and correlations.

Convolutional neural networks, which are subset of deep neural networks, proved to be successful in classification and recognition tasks. The convolution operation in terms of image processing is a filtering process. A filter (convolution mask) is moved through the image and the sum of products of the corresponding values is calculated. Parameters are usually the window (mask) size and the number of pixels by which the mask moves in each step. The goal of the first convolution layers is to reveal general image features such as edges and simplest shapes. Those deeper ones can already indicate whole shapes and high-level features.

Transfer Learning

Deep neural network models require not only computational resources but also huge amount of training, validation and testing data in order to tune all parameters well which is the main limitation in building deep networks from scratch Moreover, sometimes an experiment cannot be repeated or data gathering can be dangerous or very expensive so often scientists end up with a limited amount of data. While observing the ability of DNN to generalize on big datasets one of the possibilities is to use transfer learning. Its main idea is to share base model of a neural network, build only classifier on top of it and by this architecture solve similar issue [11].

The decision of choosing the transfer-learning strategy has been done based on the amount of data in the dataset. I have also decided to use the soft fine-tuning strategy. Main idea is to unlock some of the layers of base model and train both new classifier on top and those few layers (original weights are used as a starting point). This method can improve models' performance by tuning architecture to its new task. Taking into account that the pre-trained model has been well trained on a huge database I kept a small learning rate (only for the classifier) to ensure that I don't distort the CNN weights too much.

Proposed Beam Profile Classification Solution

The main purpose of the proposed solution is automatically assess and classify transverse beam profiles based only on the evaluation of the beam image from the Pinhole diagnostic beamline. Due to the complexity of the operation, Solaris has a distributed control system that gathers diagnostic signals from thousands of devices, processes them and finally controls many setpoints and moving elements. Measurement data from most devices are read and archived using dedicated archiving system. Different kind of signals (scalars, 1D or 2D) are stored in the database and are easily accessible for further analysis and comparison.

For the emittance and beam size monitoring and measurements Pinhole diagnostic beamline has been setup. It is based on X-ray radiation extracted from the dipole through a diamond window, a pinhole cross down to the scintillator crystal where is converted to the visible light. The optical light from scintillator is imaged by a CCD camera [12]. Overview of the Pinhole beamline has been shown in Fig. 2. The Pinhole beamline allows for online monitoring of the transverse beam profile and the emittance thus beam stability during electron beam decay. Example of data extracted from this diagnostic beamlie at Solaris has been shown in Fig. 3.

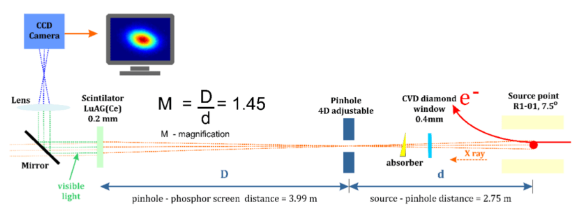
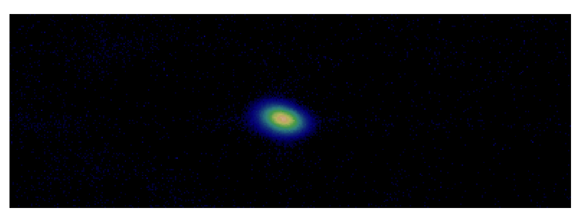
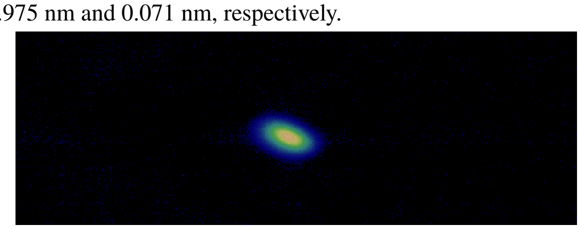


Figure 2: The Pinhole diagnostic beamline [12].



(a) High beam quality, horizontal and vertical emmitances are 9.975 nm and 0.071 nm, respectively.



(b) Low beam quality, horizontal and vertical emmitances are 15.047 nm and 0.093 nm, respectively.

Figure 3: Example images taken by the Pinhole diagnostic beamline in Solaris Radiation Centre.

Database for this research has been created from scratch, gathering raw transverse beam profiles from the CCD camera

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as well as both vertical and horizontal emmitances. Following with the Solaris archiving standards and requirements, data were collected with a period of 3 s. Presented architecture has been trained using nearly 137000 Pinhole images and the corresponding emittance values. As the emittance is an important property of the beam, directly determining its quality and stability it was used to label the dataset by thresholding both horizontal and vertical emittances. Good quality beam threshold values were determined empirically and are: [5 nm, 11 nm] and [0.05 nm, 0.08 nm] for horizontal and vertical emittances, respectively. Finally, image is considered as anomaly if the emittance values go beyond the specified range in both planes simultaneously.

Architecture for Pinhole diagnostic images evaluation has been created in soft fine-tuning strategy using InceptionV3 as a base model. To achieve better performance, apart from the classifier, last three layers of the base network have been unfrozen and subjected to training. The system operation diagram has been presented in Fig. 4.

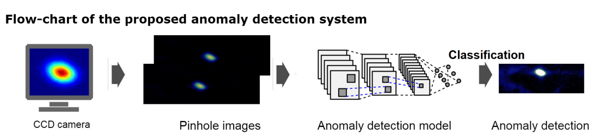

Figure 4: The streamline of proposed neural network based framework.

In the proposed system, the classifier has been created specifically for the problem of recognizing two classes: correct and not correct beam shape. It consists of three layers. The first is the Fully-Connected layer with ReLU activation function, the next is the Dropout layer and the classifier finishes the Fully-Connected output layer with two outputs and the Softmax activation function. At each of these outputs, the network calculates the probability that the input image is an anomaly or is correct. Hyperparametes setting for the proposed system has been shown in Table 1.

Table 1: Overview of the Hyperparameters Settings for the Proposed CNN Model

Parameters	**InceptionV3**
Topological depth	189
Input shape	134, 390, 3
Dropout rate	0.2
Epochs	50
Loss function	Categorical cross-entropy
Metrics	Accuracy
Fine-tuning	Last three conv-layers
Optimizer	Adam

Tests and Results

At the stage of preparation and initial data processing, two datasets have been obtained: training and validation. They come from completely different periods of time, which ensures the reliability of the results obtained in tests. Accuracy of the proposed system is 95.20% and 94.10% for those datasets respectively, which shows that the network classifies images very well. Moreover, it can also be concluded that the system was not overfitted. For further evaluation of the model, confusion matrix was created (see Table 2). The system should have as many classifications as possible on the diagonal of the confusion matrix (correct classification), and when there is a mistake it should be FP (false positive) type. It means that it is a false alarm which can be easily verified by duty operator.

Table 2: Confusion Matrix

Actual class	**Predicted class** positive	negative
positive	62037	3559
negative	6574	100592

CONCLUSION AND FUTURE WORK

The paper presents the design of deep neural network based system for transverse beam profile classification. It was inspired by earlier research conducted using various machine learning and deep learning techniques in accelerators. It has been proved that using deep neural network based systems can achieve high accuracy in electron beam quality assessment. What is worth emphasizing is a fact that it can be done based directly from raw Pinhole image without having to calculate any physical beam parameters. Such a system could certainly serve as a support for the Operators giving valuable information on the current machine performance.

The system has great development potential. The next stage will be real time Pinhole image capturing and their classification. Further modifications may include extending the number of classes to find more meaningful and potentially useful beam states for the Operators and to include the Solaris' state machine.

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