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DEEP NEURAL NETWORK FOR ANOMALY DETECTION IN ACCELERATORS

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Abstract

The main goal of accelerators like SOLARIS is to provide scientific community with high quality synchrotron light. In order to achieve this it is essential to monitor subsystems that are responsible for beam stability. In this paper, a deep neural network for anomaly detection in time series data is proposed. A pre-trained, 19-layer convolutional neural network called VGG-19 has been chosen. The main aim is to identify abnormal status of sensors in certain time step. Each time window is a square matrix so can be treated as an image. Any kind of anomalies in synchrotron's subsystems may lead to beam loss, affect experiments and in extreme cases can cause damage of the infrastructure, therefore when anomaly is detected operator should receive a warning about possible instability.

INTRODUCTION

The National Synchrotron Radiation Centre functions under the auspices of the Jagiellonian University (Fig. 1). The main goal of SOLARIS is to provide the scientific community with high-quality synchrotron light for research. At the moment SOLARIS has two beamlines PEEM/XAS and UARPES, and four more are under construction or are planned. The PEEM/XAS is a bending magnet based beamline dedicated to microscopy and spectroscopy in the soft X-rays energy range. Ultra angle-resolved photoemission spectroscopy beamline allows for measurements of fundamental quantities, i.e. the energy and the momentum, describing a photoelectron state in the space outside the solid sample.

Figure 1: NSRC SOLARIS [1].

Synchrotron is a complicated and complex device that requires the use of a distributed control system. To obtain a stable beam it is necessary for all subsystems to work correctly. Proper calibration is possible thanks to hundreds of diagnostic signals, which carry a lot of important information about the state of the machine. However, manual inspection performed even by an experienced operator is not able to extract full information from them. 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.

The use of artificial intelligence techniques, including machine learning and neural networks, for signal analysis, prediction or anomaly detection has a long history. Also in the accelerator field BigData is being developed and finds applications in existing problems that engineers and scientists are struggling with. Neural networks used to correct beam orbit were proposed in a synchrotron in Australia [2]. This model consists of two neural networks trained on archived beam position data in the storage ring to determine the appropriate correction in such a way as to minimize losses described by the cost function. The topic of detection of anomalies in the control system has been raised at the last ICALEPCS Conference in 2017 by CERN [3]. The authors proposed three different mathematical approaches that have been designed and developed to detect anomalies. Those methods are dynamic, as behaviour of the system is changing in time, unsupervised detection systems for finding anomalies in live data.

ANOMALY DETECTION SYSTEM

In this section an anomaly detection model based on deep, convolutional neural network is presented. Main idea behind is to treat a bunch of diagnostic samples as an image and use transfer learning methods to build suited classifier on top of the pre-trained architecture.

Neural Networks

In recent years, 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

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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.

Transfer Learning

Deep neural network with many hidden layers require huge amount of data to learning process. In order to use those architectures in cases where data is limited, transfer learning has been introduced. The main idea behind it is to take a trained model that has been trained on a similar dataset to solve a certain problem. All that has to be done is to build personalized classifier on top of the pre-trained model. If more data is available fine-tuning is possible, which means that some of the frozen layers can be additionally trained. A breakthrough in the creation of such models came in 2012, when the AlexNet a deep, convolutional neural network has been firstly presented during the ImageNet event [4]. Similar architectures have proved to be effective in the field of photo or video processing, classification and shape recognition. Over the years, many models and architectures have been implemented and proposed to public use (Fig. 2).

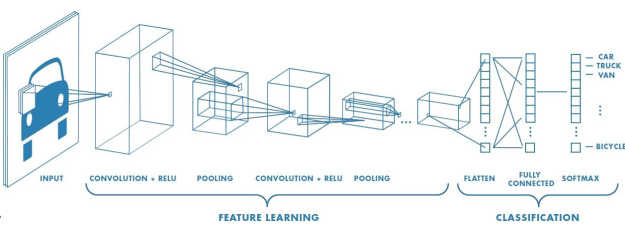

Figure 2: Deep, convolutional neural network [5].

One of them has been created at the University of Oxford, where the VGG (Visual Geometry Group) was formed. As part of the ImageNet Challenge event in 2014, two deep, convolutional neural networks have been presented: one with 16 layers (VGG16) and the other 19 (VGG19). A very large collection of photos - about 1.3 million - was used for training. This network can classify the input data into one of a thousand classes. The proposed solution turned out to be very effective in both the task of classification and detection, which allowed it to take first and second place. In addition, VGG models have high generalization capabilities and can work properly for a wide range of datasets. This is one of the reasons why those architectures have gained great popularity and are used as base models [6]. These pre-trained networks are available in Caffe, MATLAB or Tensorflow.

Convolutional Neural Network

Convolutional 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.

Another type of layer characteristic for convolutional neural networks is the pooling layer. Its main task is to select the dominant features indicated by the convolution layers as well as to reduce dimensions, which translates into a reduction in computing power needed and efficient operation even for large data sets. There are two types of pooling layers: max pooling and average pooling. The first of them, moving the window through the image, selects the highest pixel value from the window, while the second calculates the arithmetic mean of the pixel values from the window (Fig. 3).

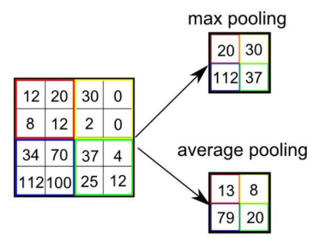

Figure 3: Pooling layers [5].

The last element of the architecture of the convolutional neural network is the classifier. It usually contains a Fully-Connected (FC) layer that connects every neuron in one layer to every neuron in another layer. The number of network outputs corresponds to the number of classes into which the developed network should classify the input images. The use of the Sotfmax activation function allows for each output to obtain the probability that the object belongs to a given class.

Anomaly Detection Solution

The main purpose of the proposed solution is the detection of anomalies in signals coming from the measuring devices in the SOLARIS synchrotron and as a result the detection of beam instability. Due to the complexity of the synchrotron operation and the number of subsystems necessary for its proper operation, it has a distributed control system. Measurement data from most devices are read and archived in the database. One such key subsystem is the vacuum subsystem. Sample measurements have been presented in Fig. 4.

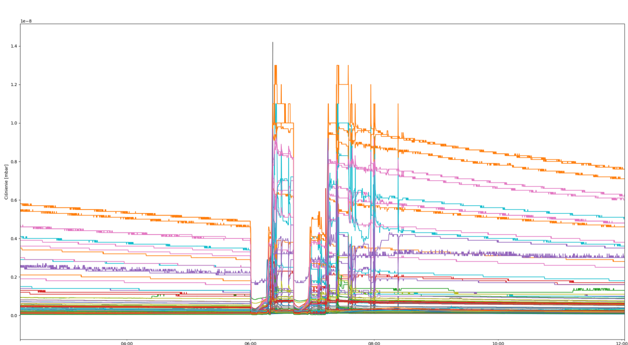

Figure 4: Example readings from vacuum subsystem.

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The base concept of the proposed system is the fact that the collected measurement data from many devices at once and divided into appropriate time windows can be treated as an image (matrix of values). Therefore, the use of available algorithms and models for the purposes of classification of aggregated measurement data is authorized. In particular, this applies to deep, convolutional neural networks, whose ability to extract complex image features can help in finding those in multivariate signals. Proposed model is based on the pre-trained, deep, convolutional neural network VGG-19. Its biggest advantage is generalization for a wide range of datasets and no need to train hidden layers. The system operation diagram has been presented in Fig. 5.

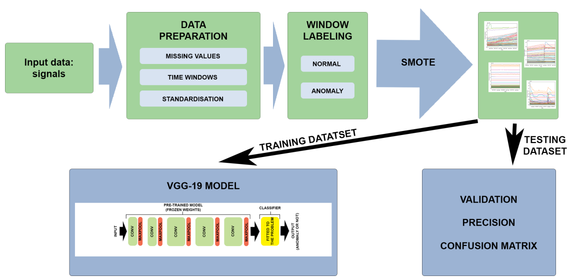

Figure 5: System diagram.

One of the most important tasks before machine learning or neural networks is proper data preparation. This allows obtaining satisfactory results of the model and also to avoid errors caused by entering the wrong or noisy data into the system. The data are pressures measured by 64 Gamma Vacuum power supplies located around the storage ring. Main part of data processing was to divide the collected measurement signals into identical time windows. Because there were 64 readings, the window size was assumed for 64 subsequent data samples. Thanks to this, square images were obtained, which can be easily used as input to the VGG-19 model. Due to the use of the supervised approach, each window prepared in this way had to be described as correct or anomaly. The assessment itself was done manually. Next step was data standardization. Example time windows has been shown in Figs. 6 and 7.

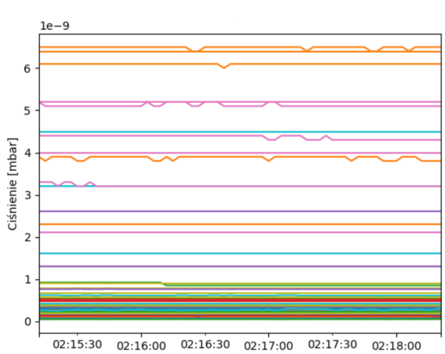

Figure 6: Time window without anomaly.

One of the difficulties encountered during the construction of the anomaly detection system was the data set imbalance

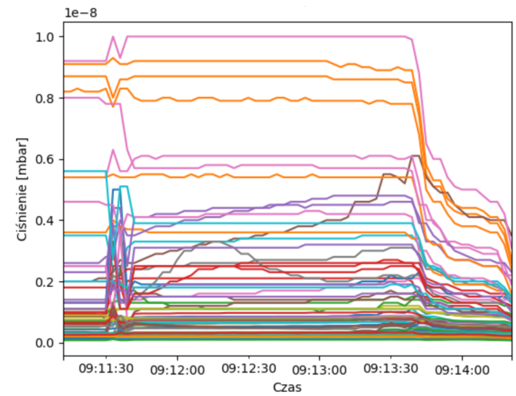

Figure 7: Time window with an anomaly.

between the anomalies and non-anomalies. Using such data to teach the model could result in incorrect operation of the system, which would be insensitive to windows that are anomalies and would give erroneous, high results. One of the techniques to solve the problem of unbalanced classes is the SMOTE algorithm (Synthetic Minority Over-sampling Technique) which works by generating new, synthetic data [7].

In the proposed system, the classifier has been created specifically for the problem of recognizing two classes: anomaly and correct signal. It consists of three layers. The first is the Fully-Connected layer with ReLU activation function, the next is the Dropout layer [8] 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 correct signal (Fig. 8).

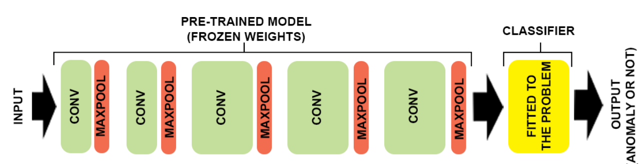

Figure 8: Proposed architecture.

Tests and Results

At the stage of preparation and initial data processing, two data sets have been obtained: training and test. They come from completely different periods of time, which ensures the reliability of the results obtained in tests. In both sets, the classes have been balanced using SMOTE algorithm. In addition, for the purposes of optimizing model parameters the validation set was created. Accuracy of the system for training dataset is 96.70%, for validation one 98.35% and finally for testing 95.13%. Very high results of the proposed model have been achieved. Based on them, it can also be concluded that the system was not overfitted. For further evaluation of the model, confusion matrix was created (see Table 1). 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.

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Table 1: Confusion Matrix

Actual class	Predicted class	
	positive	**negative**
positive	820	2
negative	78	744

Figures 9 and 10 present the classification of time windows by the proposed anomaly detection system applied to the original signals. The time of detection of the anomaly is closely related to the construction of the time window. The time window of 64 samples is about three minutes so this is the maximum time after which the system should detect the anomaly. Fragments qualified as positive results are marked in red.

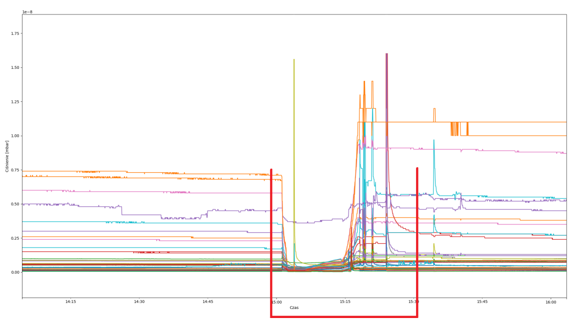

Figure 9: Time window with detected anomaly.

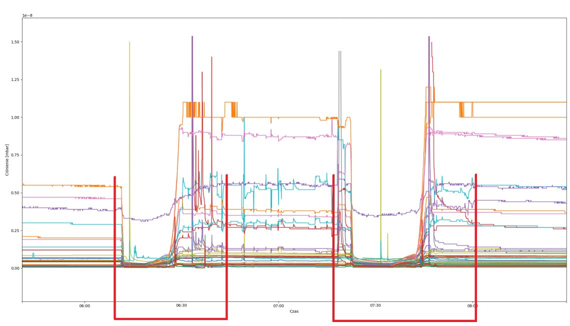

Figure 10: Time window with detected anomalies.

Tests have shown that the system based on the deep, convolutional neural network VGG-19 correctly classifies time windows of multivariate signals. It is characterized by high accuracy of over 90%. Mistakes are mostly false alarm (FP - false positive). This is a very desirable property for a system that detects anomalies and situations that are potentially dangerous for infrastructure. Time to detect anomalies in the data is related to time window construction and can be up to three minutes. Tests have also shown that, except for the learning part which can be up to couple minutes, the classification of time windows is very fast.

CONCLUSION AND FUTURE WORK

The paper presents the design of the anomaly detection system in the multivariate signals of the SOLARIS synchrotron. It was inspired by earlier research conducted using various machine learning techniques to predict and classify anomalies and potentially dangerous situations in accelerators. The proposed solution is based on the deep, convolutional neural network VGG-19. It is a pre-trained network with optimized weights, with high generalization capabilities. It has been shown that a set of measurements in a certain time window can be treated as an image. The VGG-19 network with data prepared in this way allows detecting anomalies in signals. In addition, it was pointed out that the possibilities of adapting architecture to own needs by using transfer learning are so large that the class of problems to which VGG-19 can be used as the base model is very wide.

The system has great development potential. The next stage will be operation in real time so aggregation of the measurements into time windows and their classification. Further modifications may include extending the number of classes in such a way as to include the SOLARIS' state machine and by that better adapt to the specifics of the machine operation.

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