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3D Convolutional and Recurrent Neural Networks for Reactor Perturbation Unfolding and Anomaly Detection.

mlearn
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CORTEX
Core monitoring techniques and experimental validation and demonstration

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Background

With Europe's ageing fleet of nuclear reactors running closer to their safety limits, the monitoring of such reactors through complex models has become of great interest to maintain a high level of availability and safety. Advanced modelling software has been employed to simulate different scenarios inside *Pressurised Water Reactors (PWR)* outputting detector readings of the induced neutron noise. These simulations have been designed and ran by collaboratory partners each utilising bespoke simulation software to provide data in both the time and frequency domain, each through the use of Simulate-3K [1] and CORE-SIM+ [2] respectively. From this, we propose an end-to-end deep learning architecture for the classification and localisation of reactor perturbations and their sources from the induced neutron noise signals.

The proposed architecture is comprised of two models, each tackling either the *time* or *frequency domain*. A multi-task, densely connected, *3D-Convolutional Neural Network (CNN)* has been employed for the frequency domain. The convolutions provide spatial feature extraction from the volumetric frequency input, classifying and localising based on a feature vector representation of the input volume. In the time domain, Long Short-Term Memory (LSTM), *Recurrent Neural Networks (RNNs)* have been employed to extract temporal features of the time-series samples for the classification of perturbation type.

These architectures extend the work conducted by the University of Lincoln, MLearn Group [3] for new and larger-scale datasets.
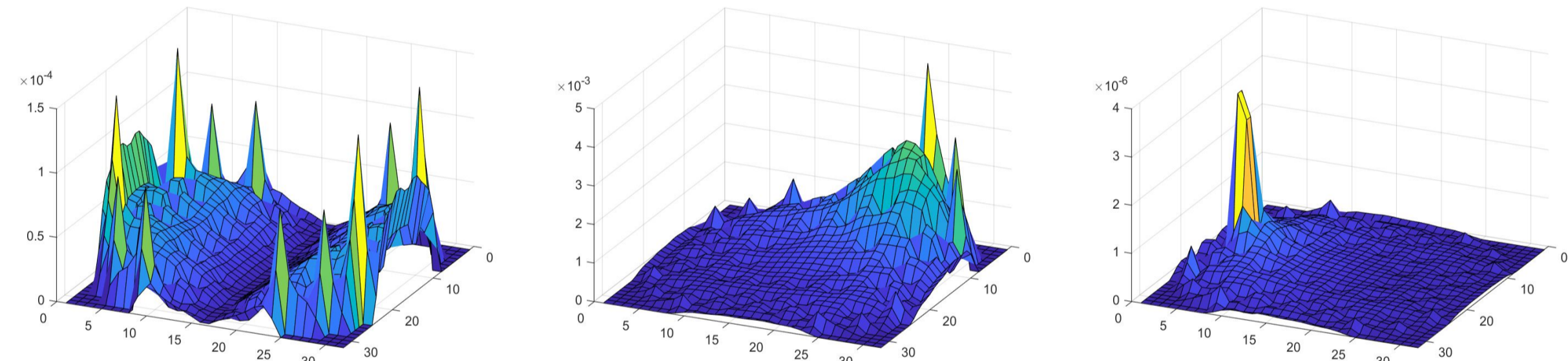

Figure 1. Examples of the induced neutron noise on the 10th axial plane shown as its amplitude.

Methodology

Convolutional Neural Network

A modified DenseNet [4] has been utilised, adapted to allow for the volumetric input. 3D-convolutions replace the 2D variant, with the network being adjusted in depth, shown in Figure 2. The dense connections allow a greater flow of information between layers, where a ℓth hidden layer H_ℓ, receives as an input the feature-maps of all preceding layers as input

$$X_\ell = H_\ell([X_0, X_1, ..., X_{\ell-1}])$$

allowing for more appropriate information about the spatial relationships in the data to be transported through the network.

From the last convolutional layer, the network outputs a feature vector of the input which feeds to the output layers via *Global Average Pooling (GAP)*. GAP directly outputs the spatial average over the feature maps, resulting in a vector $V \in \mathbb{R}^m$ where m is the number of feature maps.

Additionally, the network was trained to minimize individual losses for each task, *Binary Cross Entropy (BCE)*/negative log likelihood for classification and *Mean Squared Error (MSE)* for regression, where $\hat{y}$ is the prediction of the network and y is the true value.

$$BCE = -\frac{1}{N}\sum_{i=1}^{i=1} y_i \cdot log(\hat{y_i}) + (1 - y_i) \cdot log(1 - \hat{y_i})$$

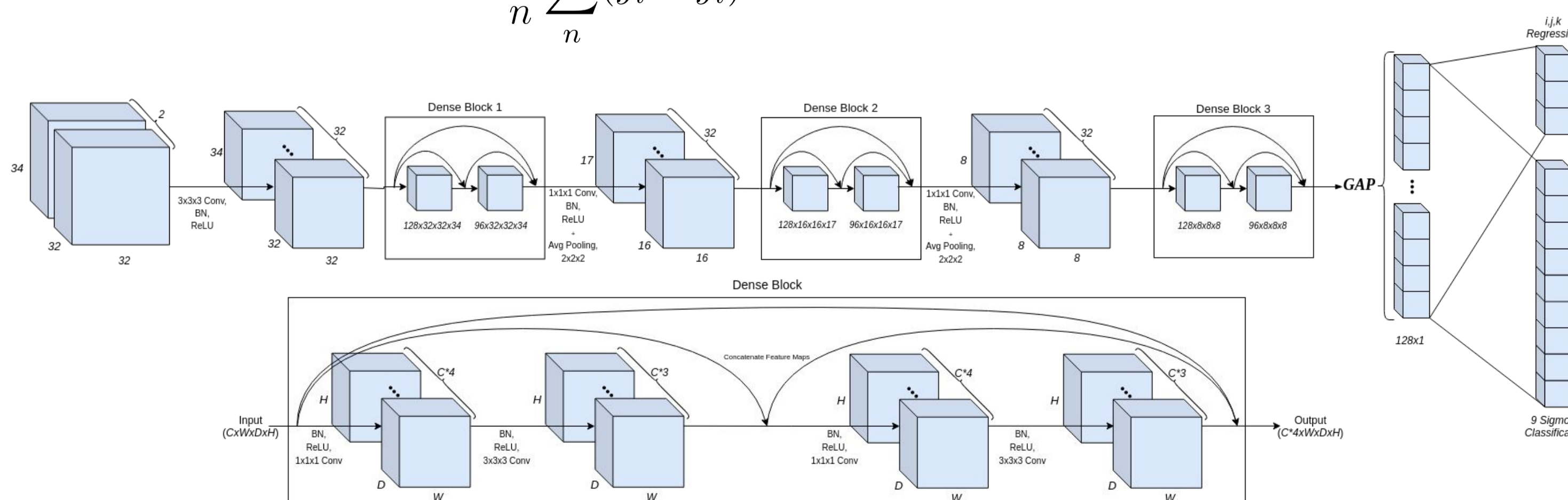$$MSE = \frac{1}{n}\sum_{n}^{i=1}(y_i - \hat{y_i})^2$$

Figure 2. Adapted CNN DenseNet for the classification and localisation of perturbation types and their sources

Recurrent Neural Networks

To learn the temporal features of the time-series signals, a stacked LSTM has been implemented. The LSTM is comprised of two layers, each with 512 hidden units, outputting a 512 feature vector to 6 sigmoid layers for multi-label classification. As with the aforementioned CNN, the BCE negative log likelihood is minimised.

RNNs learn temporal features from time-series sequences, formulating non-linear output $A^{[t]}$ from both input data $x^{[t]}$ and the activation of the previous timestep $A^{[t-1]}$, where ϕ is a non-linear activation function.

$$A^{[t]} = \phi(x^{[t]}, A^{[t-1]})$$

The LSTM units, a variation of the above RNN, have been incorporated for their ability to learn long term dependencies across long sequences, ideal for the data in question.
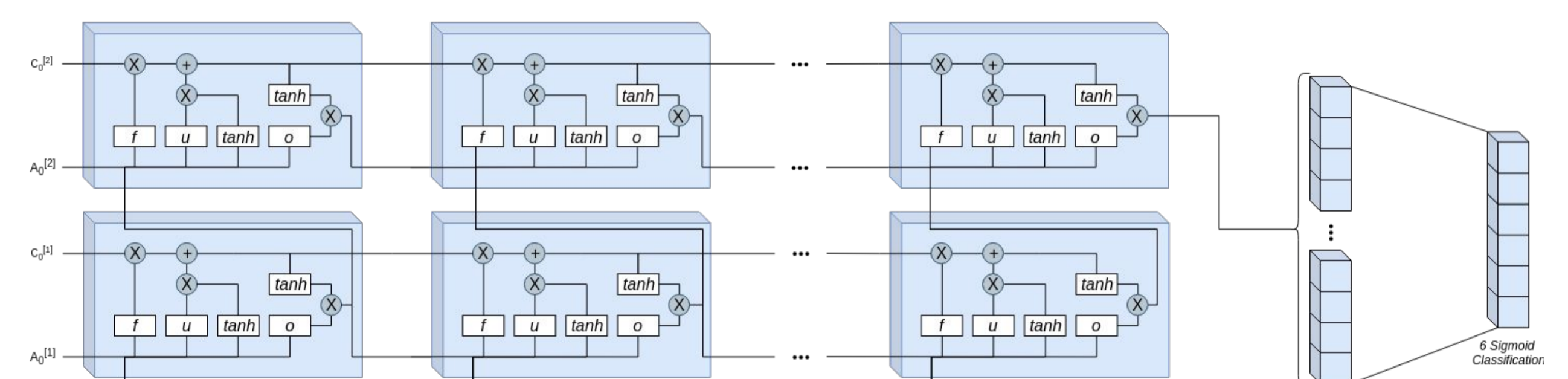

Figure 3. The proposed LSTM, RNN model for the multi-label classification of time series signals

Experimental Study

261,120 and 509,952 data samples have been provided in the time and frequency domain respectively. The frequency domain volumes were first processed to obtain the *Auto-Power Spectral Densities (APSD)* and *Cross-Power Spectral Densities (CPSD)* between the detectors. Next, the complex signals were decomposed to their amplitude and phase, the resulting signal is input as a *2x32x32x34* volume.

The time signals were augmented via sliding window sampling, with window of 100 timesteps and stride 25. Furthermore, the signals have been corrupted to study the effect of noise on proposed model.

The results of the proposed architectures can be seen in Table 1.

Frequency Domain - CNN				
Detectors	Classification F1	Accuracy (%)	Regression MAE	Regression MSE
All	0.9961	99.95	0.2048	0.1444
48 In-Core	0.9231	99.85	0.2954	0.3171
Time Domain - RNN				
Noise	Classification F1		Accuracy (%)	
No Noise	0.9363		96.41	

Table 1. Time and frequency domain experimental results. For classification higher Accuracy and F1, for Regression of Coordinates a lower MAE and MSE indicate better results.
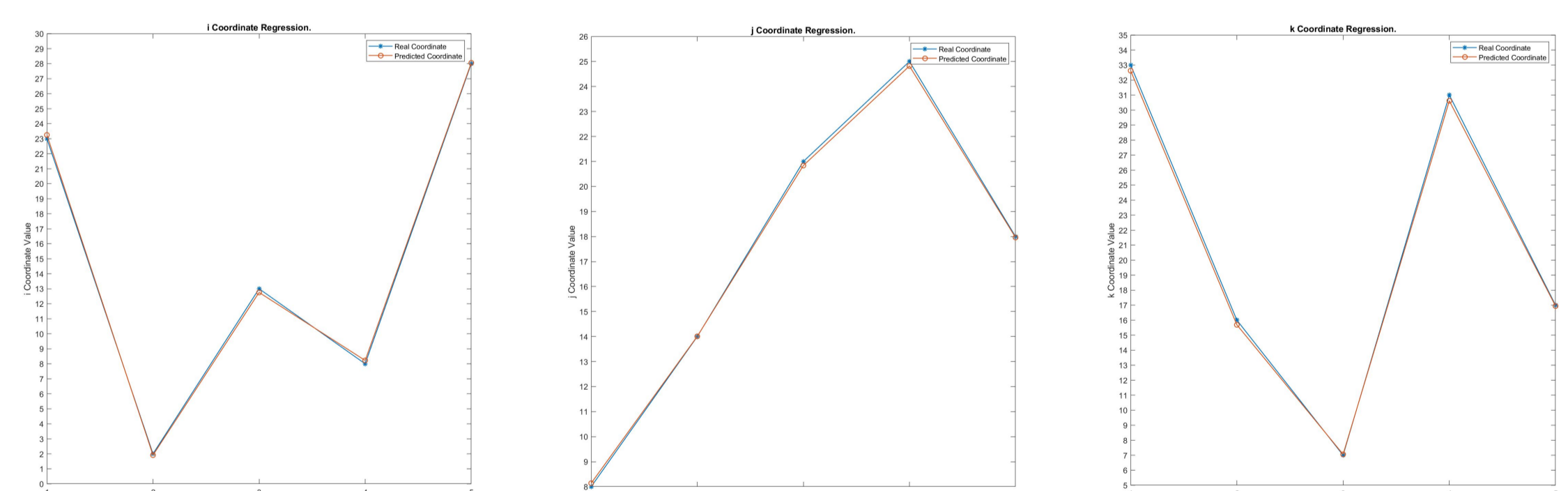

Figure 3. Predicted coordinates value against actual coordinate values (48 detectors).

Conclusion and Acknowledgements

This study presents an extension to large-scale simulated datasets for the classification and localisation of PWR core perturbation types and their sources. The results conclude the effectiveness of machine learning approaches for anomaly detection and localisation, achieving excellent results given the sparsity of detectors within the core volume. The research presented has received funding through the Core Monitoring Techniques and Experimental validation and Demonstration (CORTEX) from the Horizon 2020 project.

References

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