APPLICATION OF VIRTUAL DIAGNOSTICS IN THE FEBE CLARA USER AREA

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Motivation and Concept

- Beam characteristics at the **interaction point (IP)** are crucial to accelerator applications
- Characterised operational modes are typically used, otherwise diagnostics are integrated into applications, costing resources and limiting space in the user area
- **Virtual diagnostics (VD)** can take data away from an IP and infer properties at an IP
- Focus here is the user area at the planned **Full Energy Beam Exploitation (FEBE) upgrade to the CLARA facility** (UK) [1]
- Elegant [2] simulations create training data, for a convolutional neural network (CNN) [3], which is used to predict transverse profiles at the IP using two methods

Simulation

- Elegant [2] was used to track particles through a nominal **FEBE CLARA** [1] mode
- K1 values of several quadrupole magnets in the beamline were chosen (Fig.1)
- **Varying K1** within a range of ±20% produced a **random sample of IP beam parameters**
- Quadrupoles chosen changed IP beam parameters whilst maintaining beam transport
- Beam parameters were **captured at planned diagnostic stations**
- Keeping **simple implementation** as a focus
- Two implementation methods were targeted in this study:
  - **"Pre-IP" method**: a non-invasive beam profile diagnostic upstream of the IP to produce beam profile measurements at the IP.
  - **"Post-IP" method**: an invasive beam profile diagnostic downstream of the IP close to the beam dump, to produce upstream beam profile images of the IP.
- **10,000 pairs of beam profile images**, with their associated machine settings were generated

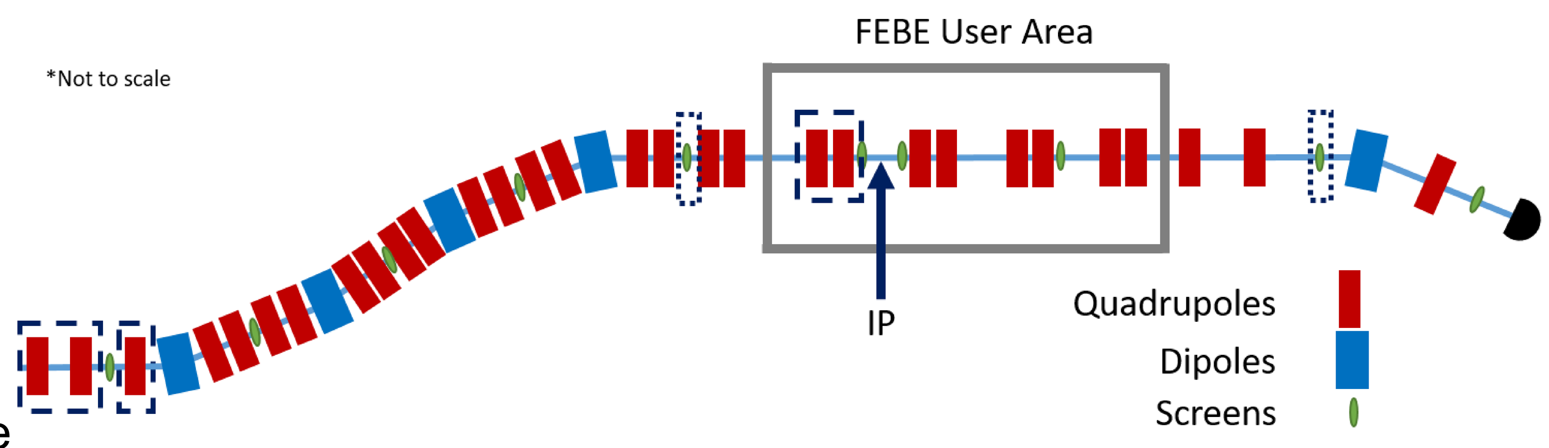

Fig. 1 – A latter section of the FEBE CLARA beamline. Quadrupoles varied and screens used in simulations are indicated.

Convolutional Neural Network

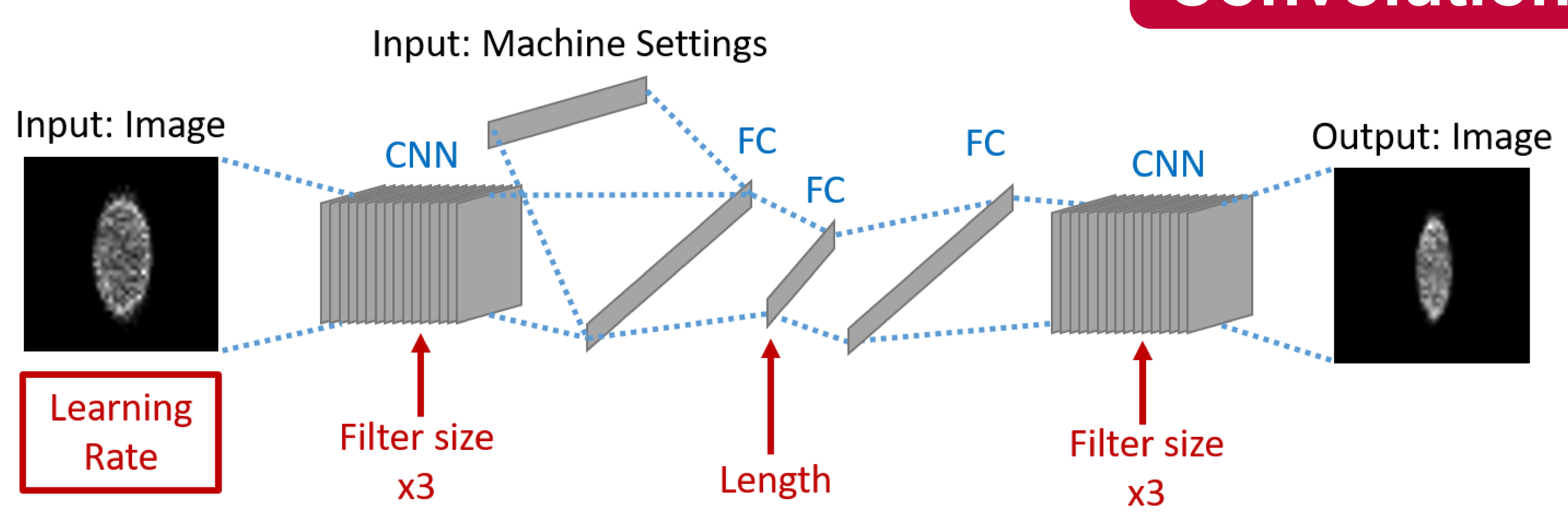

Fig. 2 – The model structure of the full tunable CNN. Tuned parameters are in red, model components in blue. CNN =Convolutional Neural Network; FC = Fully Connected.

- **CNN architecture** [3] demonstrated in Fig. 2
- Non-IP images and the machine settings taken as inputs, IP images as output
- First CNN sub-structure is comprised of convolution and maxpooling layers
- Second CNN sub-structure is comprised of convolution and upsampling layers
- Fully connected (FC) dense layers at the centre join the two CNNs together
- FC also provide an input for the machine settings
- Initially trained roughly by hand before conducting hyperband tuning
- **Hyperband** is a bandit-based approach to **hyperparameter optimisation**
- Tuned hyperparameters are shown in Fig. 2.
- Process was conducted **separately for each of the two test cases**

Results

- Trained models passed example inputs to **evaluate the IP images predicted**
- Example images of the **Pre-IP (top)** and **Post-IP (bottom)** methods are presented in Fig.3
- Left images are the input images
- Centre images are simulations from Elegant
- Right images are the model predictions
- **The transverse beam profile can be reproduced to extremely fine detail**
- **Small charge density fluctuations within the profile are predicted correctly**
- The **average RMS error**, generated by the training process, is **0.01%**
- There are **negligible differences in performance between Pre-IP and Post-IP** methods
- Implies that the reconstruction process is reversible
- Despite missing several critical parameters for a particle tracking code
- Which of the two methods to implement would be dependent upon the scenario in question

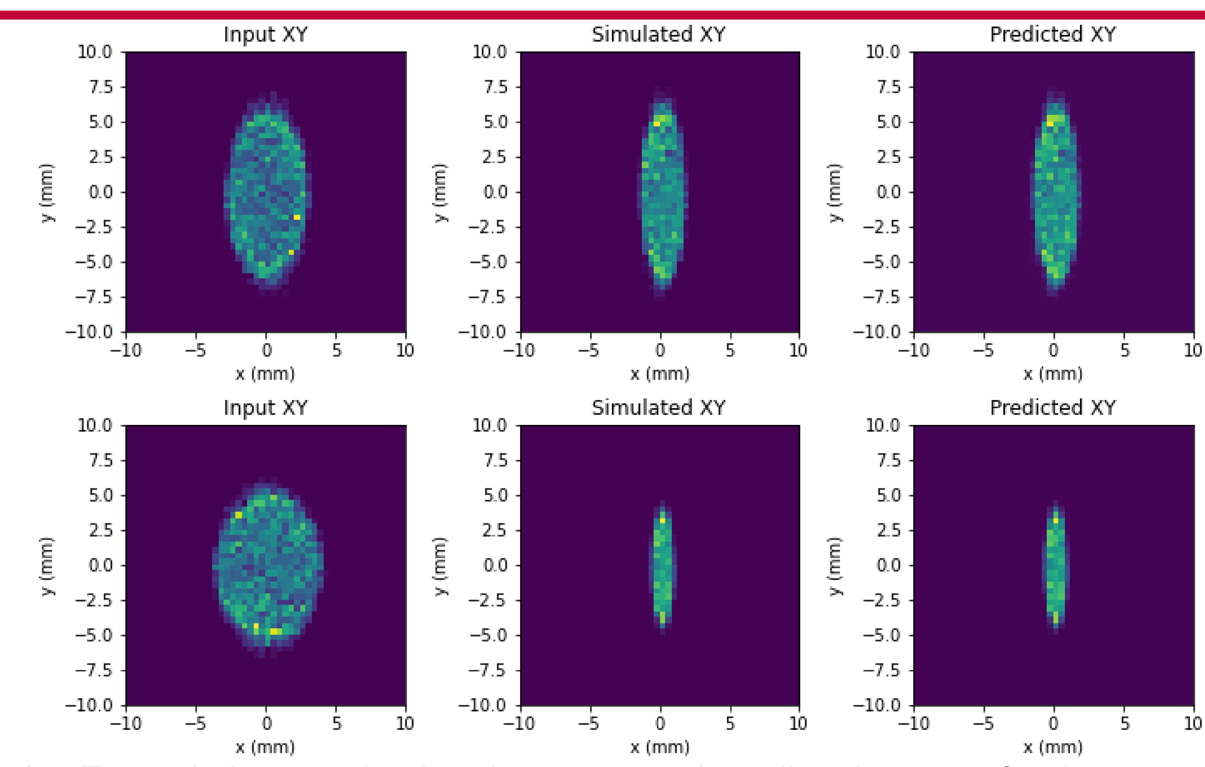

Fig. 3 – Example inputs, simulated outputs, and predicted outputs for the two models. Top: Pre-IP method. Input from FEBE CLARA transfer arc, output at IP. Bottom: Post-IP method. Input from FEBE CLARA beam dump, output at IP.

Conclusions and Next Steps

- This contribution has demonstrated a test case for the utilisation of **VD techniques to predict IP beam profiles** using measurements away from the IP
- **Further studies** are required to **increase complexity of variations** within the training data and to **include longitudinal effects**
- This framework has been constructed with this in mind, and will serve as a solid foundation for these works
- An secondary outcome of this work has also been the **predictive capability** of the CNN model, which could serve as an **operational tuning tool**
- This study has been driven by a goal of **simple implementation**
- Beam profiles are measured using standardised instrumentation, meaning the experimental measurements required to drive would often already be in place
- Including experimental and hardware limitations into these models in often a simple, yet overlooked, task
- This will **ease the transition** from training and prediction with **simulated results to practical measurables**

Acknowledgements and References

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