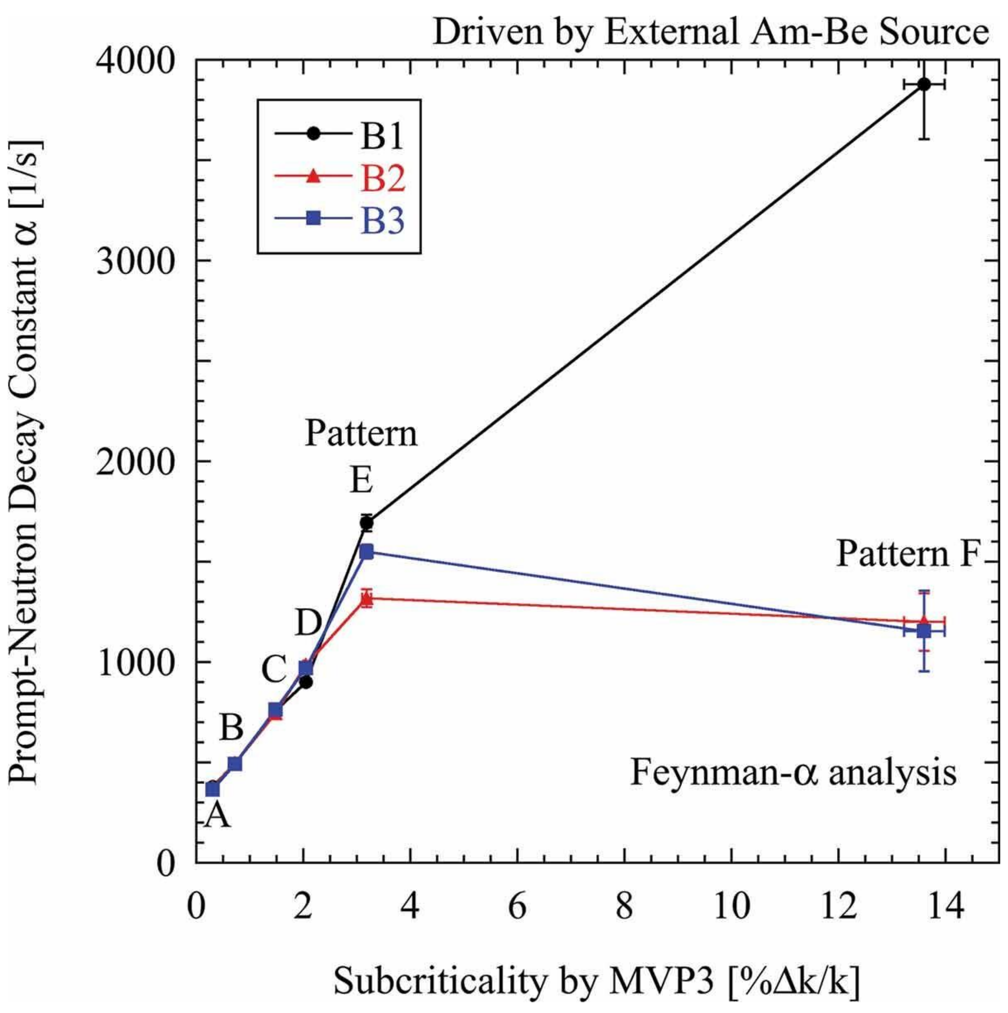
# Circumventing the limitations of reactor physics evaluation in subcritical regime with Deep Learning

*Ronald Daryll E. Gatchalian, Pavel V. Tsvetkov*

## Introduction:

Standard techniques employed in subcritical measurements are largely based on Point Reactor Kinetics in which fundamental mode flux distribution is assumed. Meanwhile, the actual flux in a source-driven system is maintained both by source and fission neutrons. This led to a bias in the obtained values using these methods due to spatial, modal, and spectral effects prominent in subcritical domain.

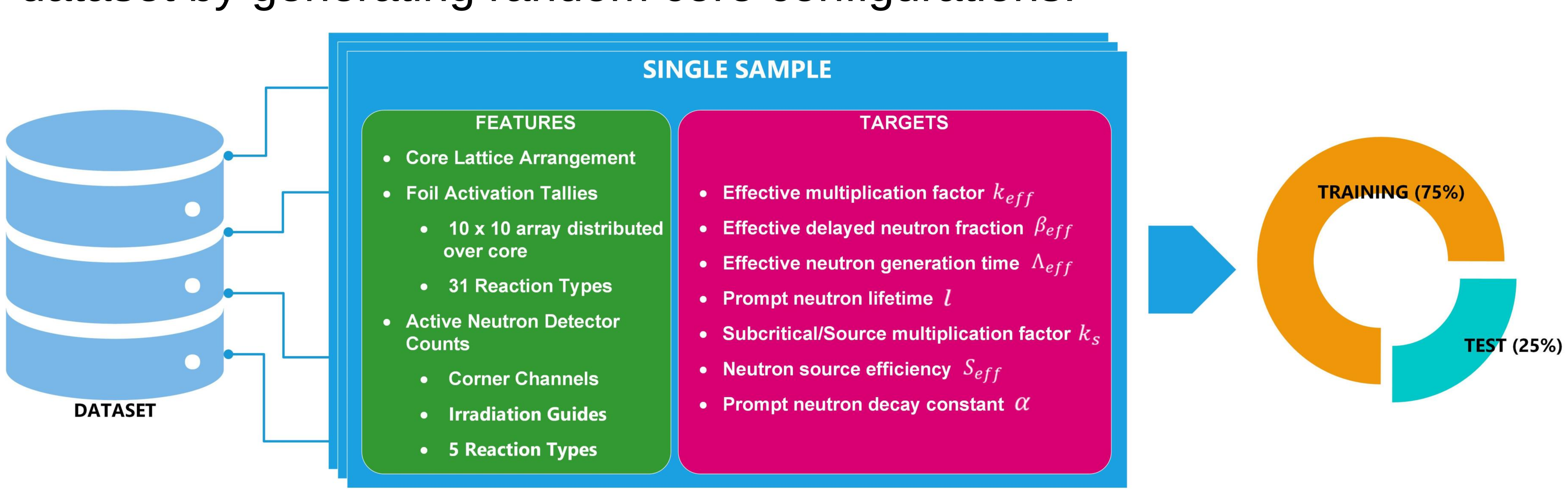



Experiment results from KUCA showing variation of measured $\alpha$ with detector location even though it is a unique value for a given subcritical state. Image adapted from [1].

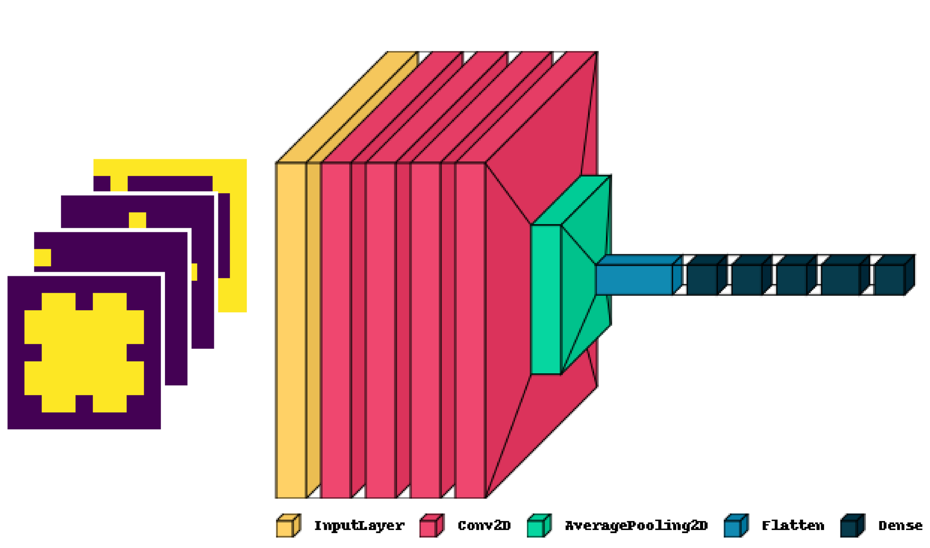
This work proposes a data-driven approach through Deep Learning to map observable quantities from experiments to integral physics parameters without being restricted to models developed for critical systems.

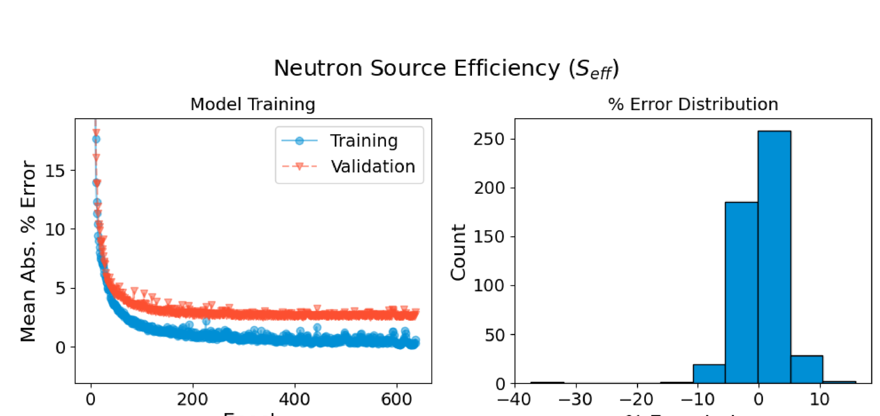
## Computational Tools & Methods:

Modelled the Philippine Research Reactor-1 Subcritical Assembly for Training, Education, and Research (PRR-1 SATER) as representative subcritical reactor and built the dataset by generating random core configurations.



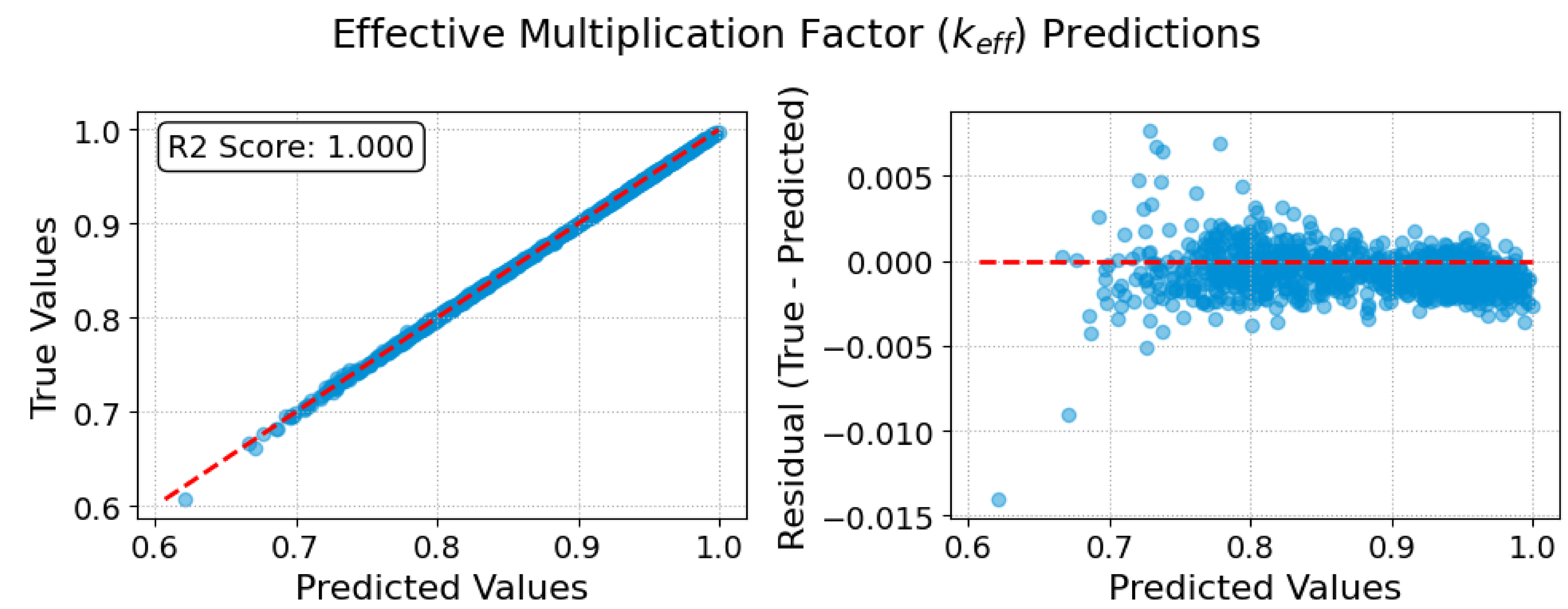

Core layout converted into image where "channels" are the component types. Higher rank tensors are natively handled by Neural Networks. Then, network topology was optimized via hyperparameter tuning to accomplish regression task.




## Results:

- $k_{eff}$ can be predicted with satisfactory Mean Abs. % Error (0.13%) and Root Mean Squared Error (149 pcm).

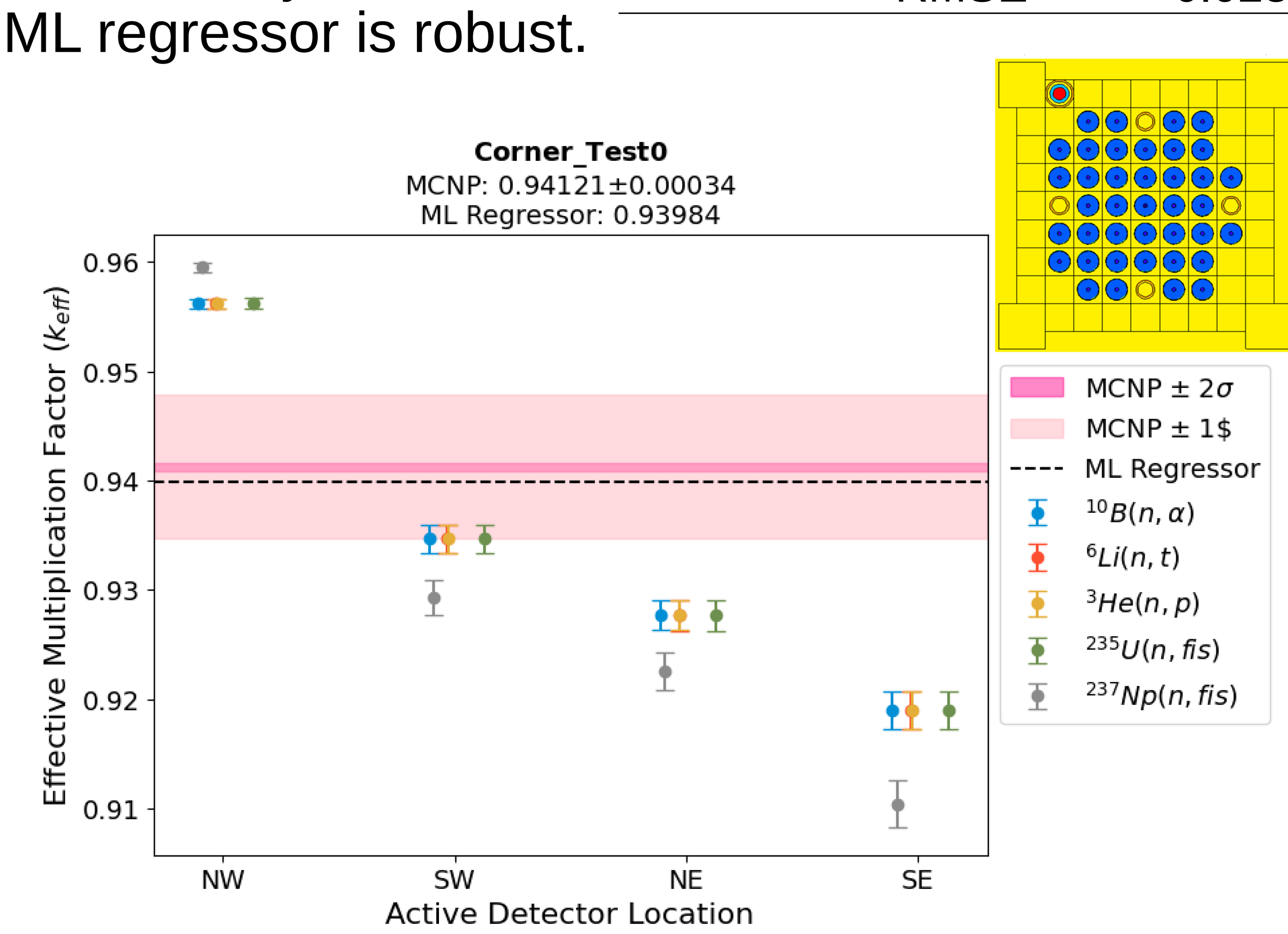



- Suitable performance on Test set across different physics quantities with just Core layout as input.
- $\beta_{eff}$ is essentially constant and exhibits trend only when $k_{eff} \ll 0.85$. (excluded)
- Physics prediction further assessed by comparison to Amplified Source Method (ASM):

$$\rho = \frac{RR_{ref}}{RR}\rho_{ref}$$

- Source at corner resulted to reduced accuracy of ASM while ML regressor is robust.

| Quantity | Metric | ML Regressor |
|---|---|---|
| $k_{eff}$ | $R^2$ | 1.000 |
| | MAPE | 0.130 |
| | RMSE | 0.00149 |
| $\Lambda_{eff}$ ($\mu s$) | $R^2$ | 0.997 |
| | MAPE | 0.956 |
| | RMSE | 0.990 |
| $l$ ($\mu s$) | $R^2$ | 1.000 |
| | MAPE | 0.148 |
| | RMSE | 0.211 |
| $k_s$ | $R^2$ | 0.996 |
| | MAPE | 0.504 |
| | RMSE | 0.00662 |
| $\alpha$ ($1/\mu sec$) | $R^2$ | 0.997 |
| | MAPE | 2.688 |
| | RMSE | 0.00005 |
| $S_{eff}$ | $R^2$ | 0.992 |
| | MAPE | 2.718 |
| | RMSE | 0.028 |




## Conclusion:

- Deep Learning predictions are insensitive against effects that arises with degree of subcriticality, and source properties to which standard techniques suffer (need correction factors).
- Physics parameters can be determined without the assumptions built into Point Reactor Kinetics, or even having known analytical relation with system observable quantity.

## References:

[1] K. Nakajima *et al.*, "Source multiplication measurements and neutron correlation analyses for a highly enriched uranium subcritical core driven by an inherent source in Kyoto University Critical Assembly," *Journal of Nuclear Science and Technology*, vol. 57, no. 10, pp. 1152–1166, Oct. 2020, doi: 10.1080/00223131.2020.1772896.

Republic of the Philippines
Department of Science and Technology
Science Education Institute
TEXAS A&M UNIVERSITY
Department of Nuclear Engineering