Multi-Task Deep Learning for Studying Nuclear Structure from UPC Vector Meson Production

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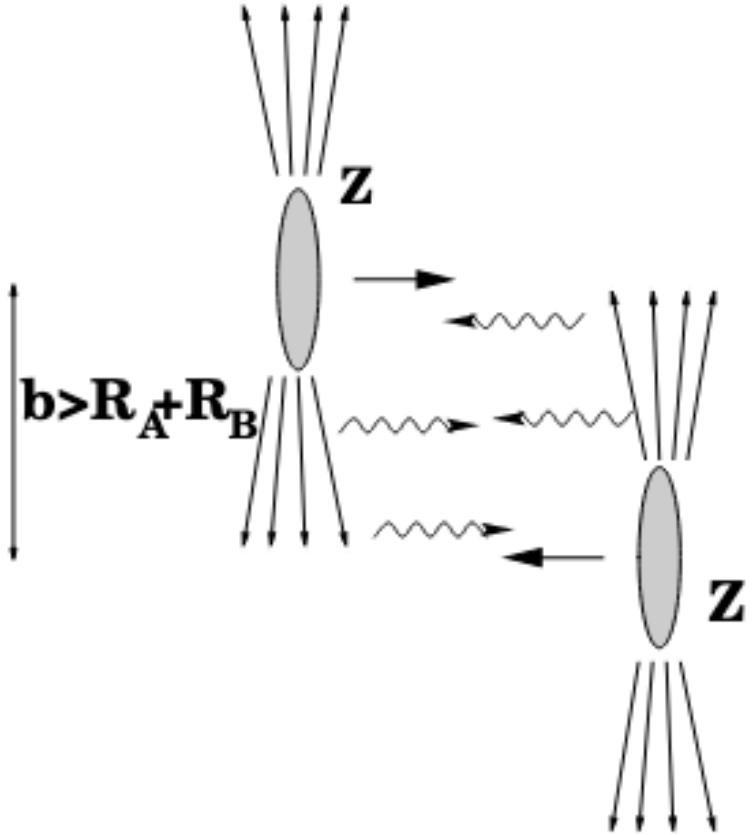
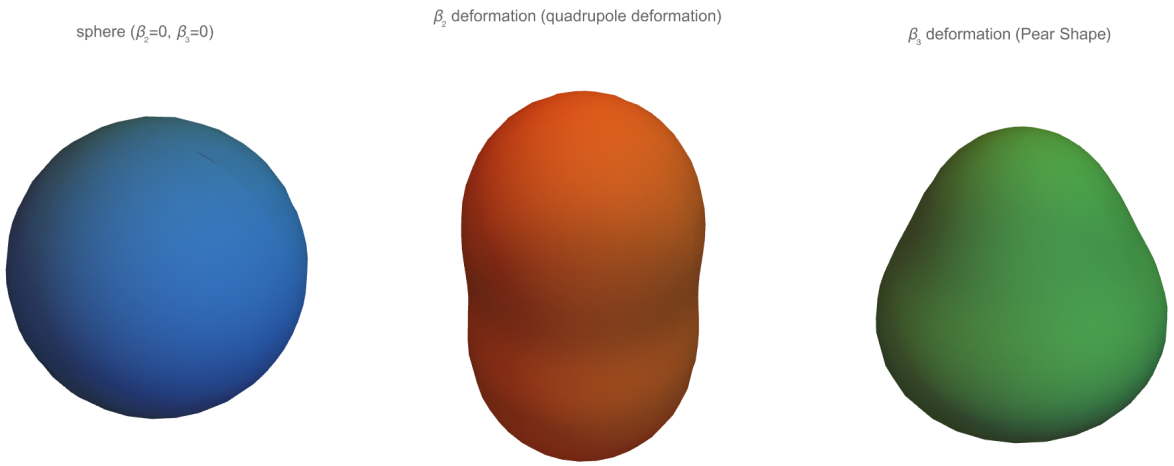
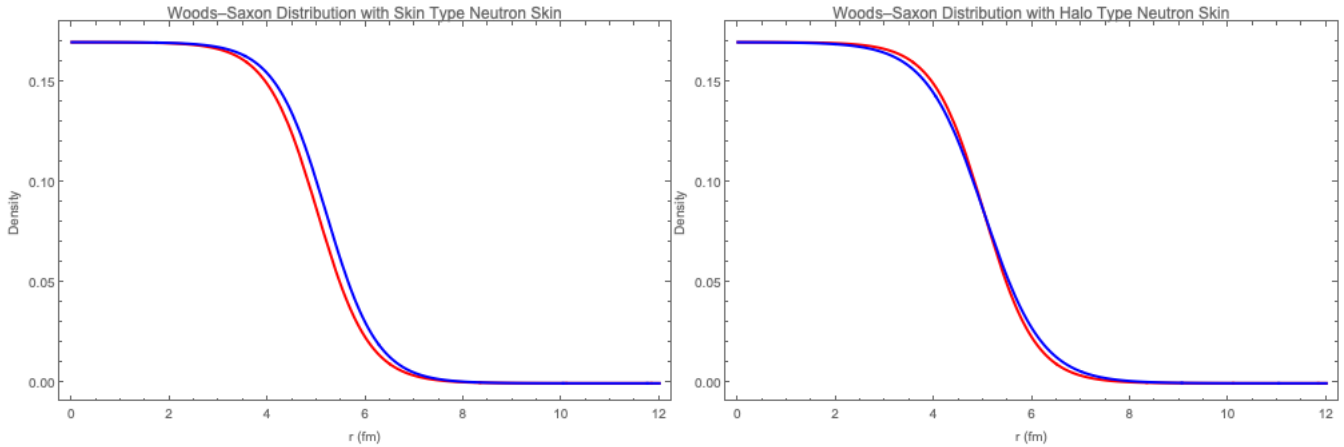
Research Background: Probing Nuclear Structure via UPCs and AI-Guided Strategy







UPC coherent production →sensitive to nuclear structure

Retrieving these parameters from final state → "Inverse Problem"

Deep Learning → decouple these parameters,

Design interpretable observables → bridge AI "Black Box" and physics

Simulation of UPC Photonuclear Processes: Double Slit Interference

density of nucleus (WS)

$$\rho_A(r) = \frac{\rho^0}{1 + exp[(r - R_{ws})/d]}$$

nuclear electromagnetic form factor

$$F(\vec{q}) = \int d^3\vec{r}\rho(\vec{r})e^{-\vec{q}\cdot\vec{r}}$$

nuclear thickness function

$$T'(\vec{r}) = \int_{-\infty}^{+\infty} dz\rho(\sqrt{\vec{r}^2 + z^2})e^{iq_L z}$$

photon flux

$$\frac{d^3N_\gamma(\omega_\gamma, \vec{x}_\perp)}{d\omega_\gamma d\vec{x}_\perp} = \frac{4Z^2\alpha}{\omega_\gamma}\left|\int \frac{d^2\vec{k}_{\gamma\perp}}{(2\pi)^2}\vec{k}_{\gamma\perp}\frac{F_\gamma(\vec{k}_\gamma)}{|\vec{k}_\gamma|^2}e^{i\vec{x}_\perp\cdot\vec{k}_{\gamma\perp}}\right|^2$$

Where $\vec{k}_\gamma = (\vec{k}_{\gamma\perp}, \frac{\omega_\gamma}{\gamma_c})$; $\omega_\gamma = M_{J/\psi}e^{\pm y}/2$

scattering amplitude

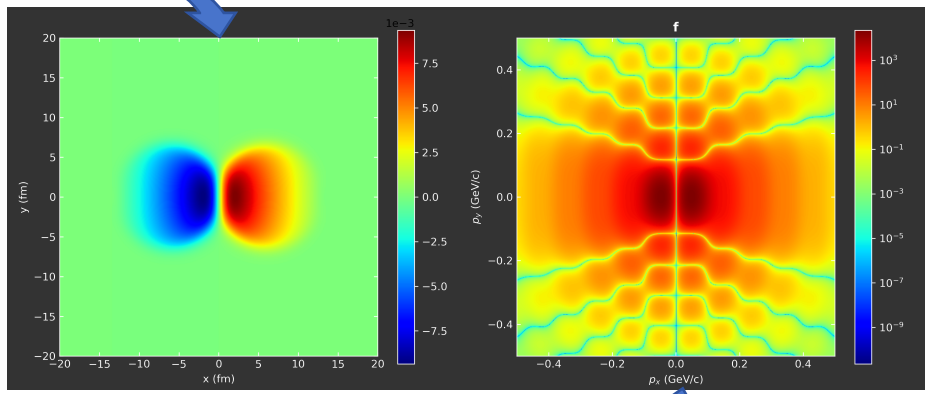
$$\Gamma_{\gamma A\to J/\psi A}(\vec{r}) = \frac{f_{\gamma p\to J/\psi N}(0)}{\sigma_{J/\psi N}} \times 2 \times [1 - exp(-\frac{\sigma_{J/\psi N}}{2} \times T'(\vec{r}))]$$

the amplitudes for J/ψ

$$A(y, \vec{r}, \pm\frac{\vec{b}}{2}) = \Gamma_{\gamma A\to J/\psi A}(\vec{r} \pm \frac{\vec{b}}{2}) \times \sqrt{\frac{d^2N_\gamma(\vec{r} \pm \frac{\vec{b}}{2})}{d^2r}}$$

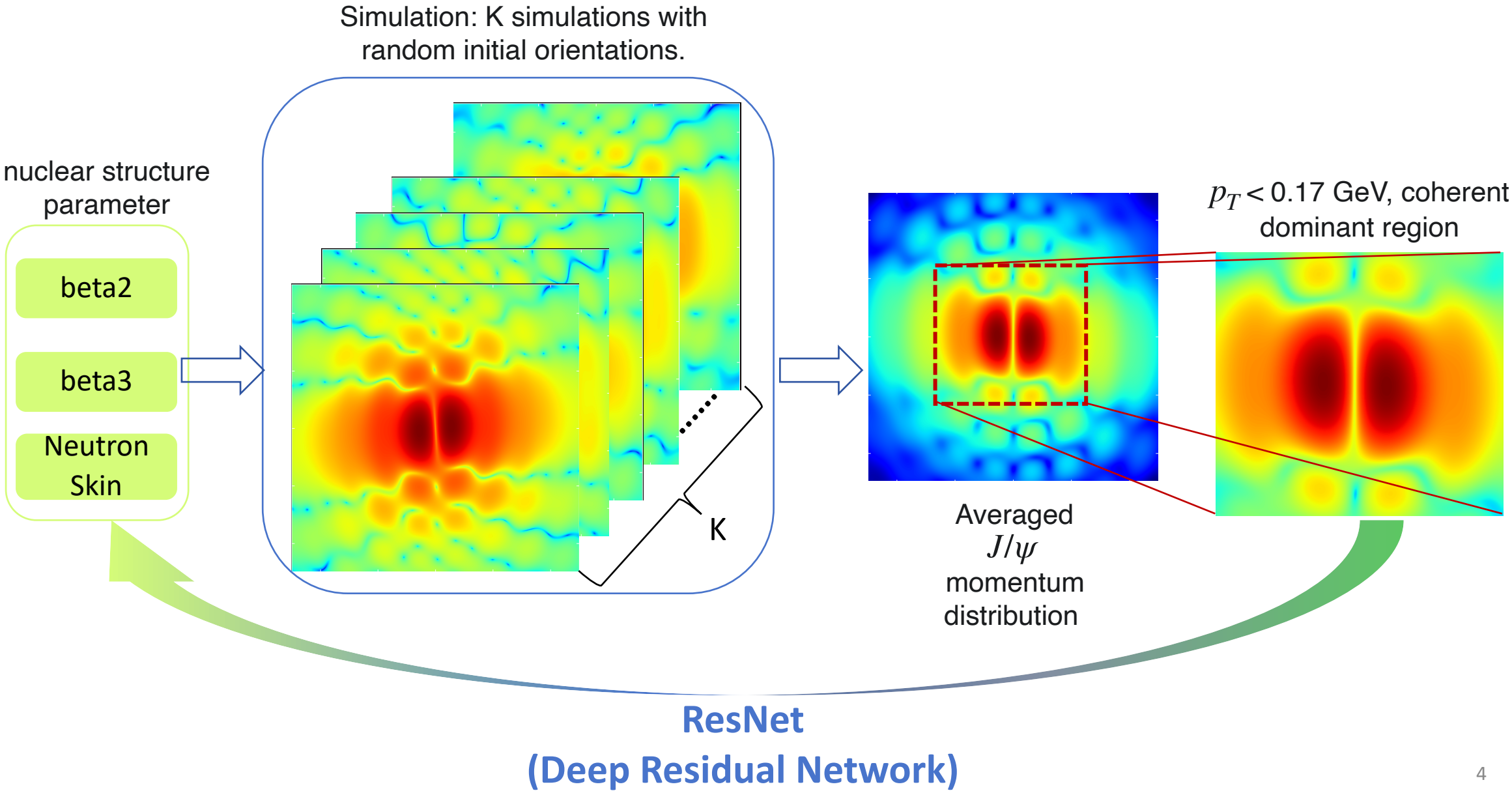
probability distribution of J/ψ in momentum space

$$\frac{d^2P}{dp_x dp_y} = \frac{1}{2\pi}\left|\int d^2r\left[A_1(y, \vec{r}, -\frac{\vec{b}}{2}) - A_2(y, \vec{r}, +\frac{\vec{b}}{2})\right]e^{i\vec{p}\cdot\vec{r}}\right|^2$$

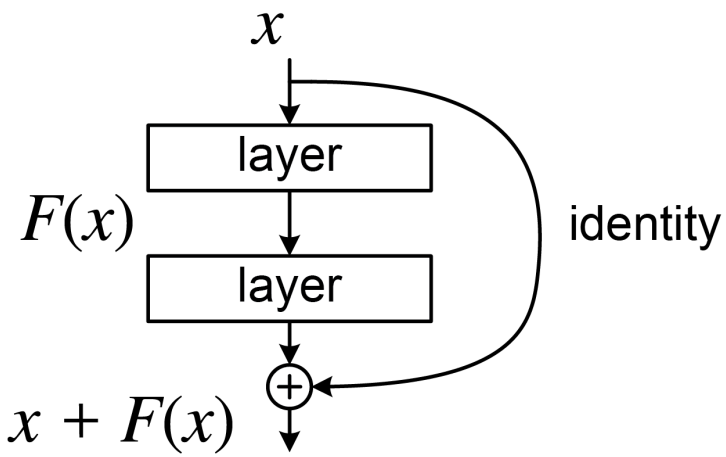


Zha et al. Physical Review C, 2019, 99(6): 061901.

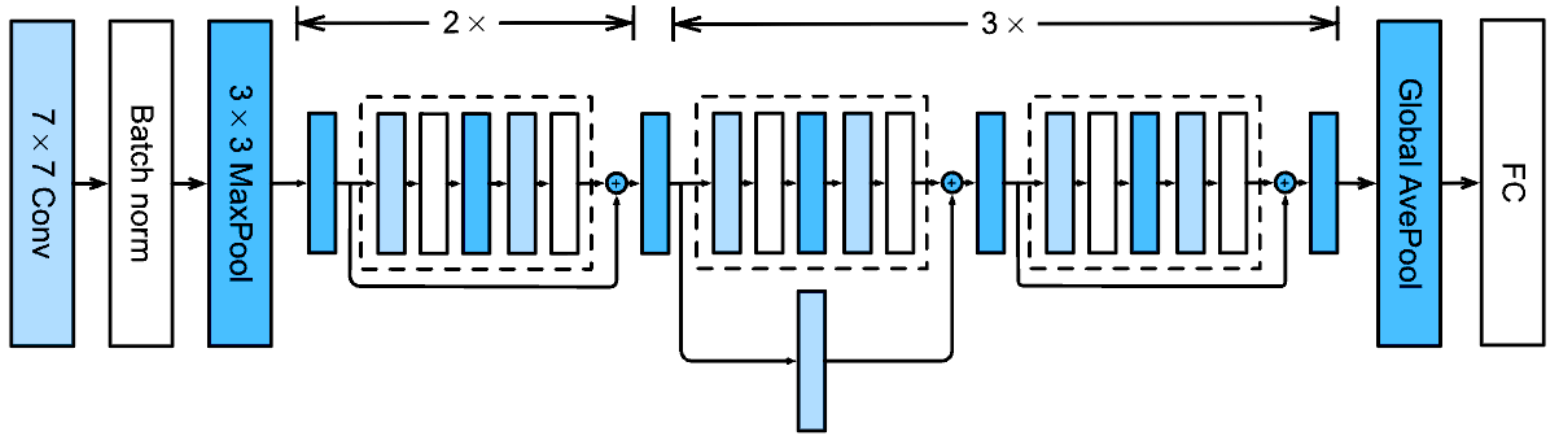
Workflow: Inferring Nuclear Structure from (p_x, p_y) Distributions



Backbone Architecture: Deep Residual Network (ResNet)



Skip Connections



ResNet model

Why use it for UPCs?

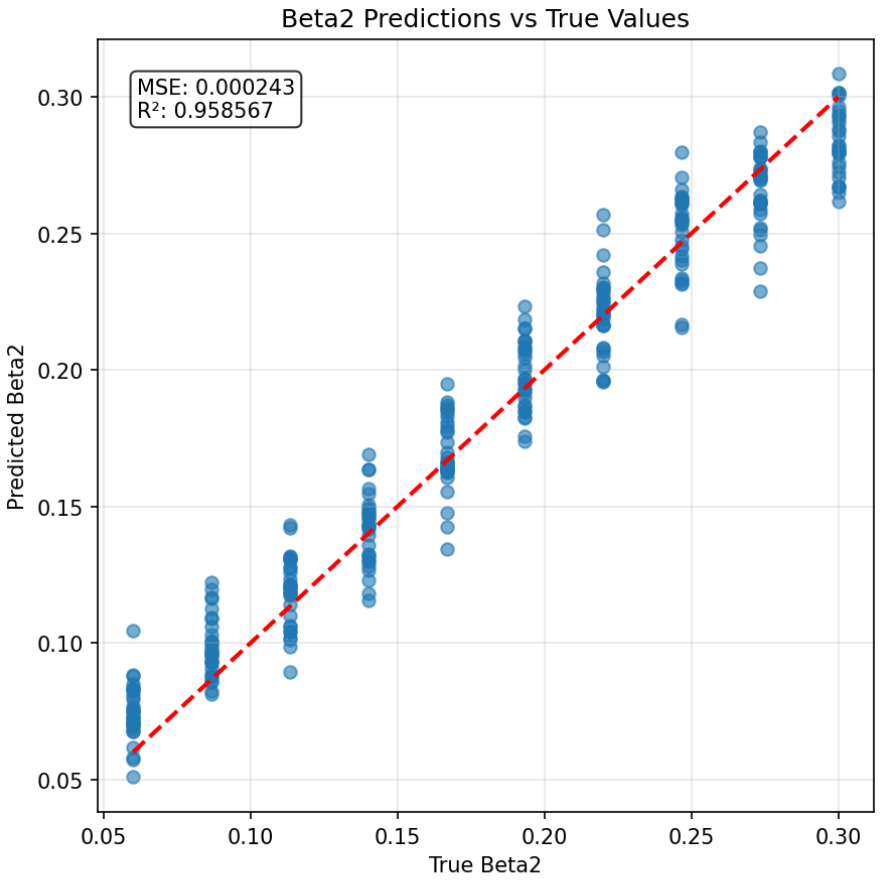
state-of-the-art: Introduces "Skip Connections" to solve the degradation problem in deep networks.

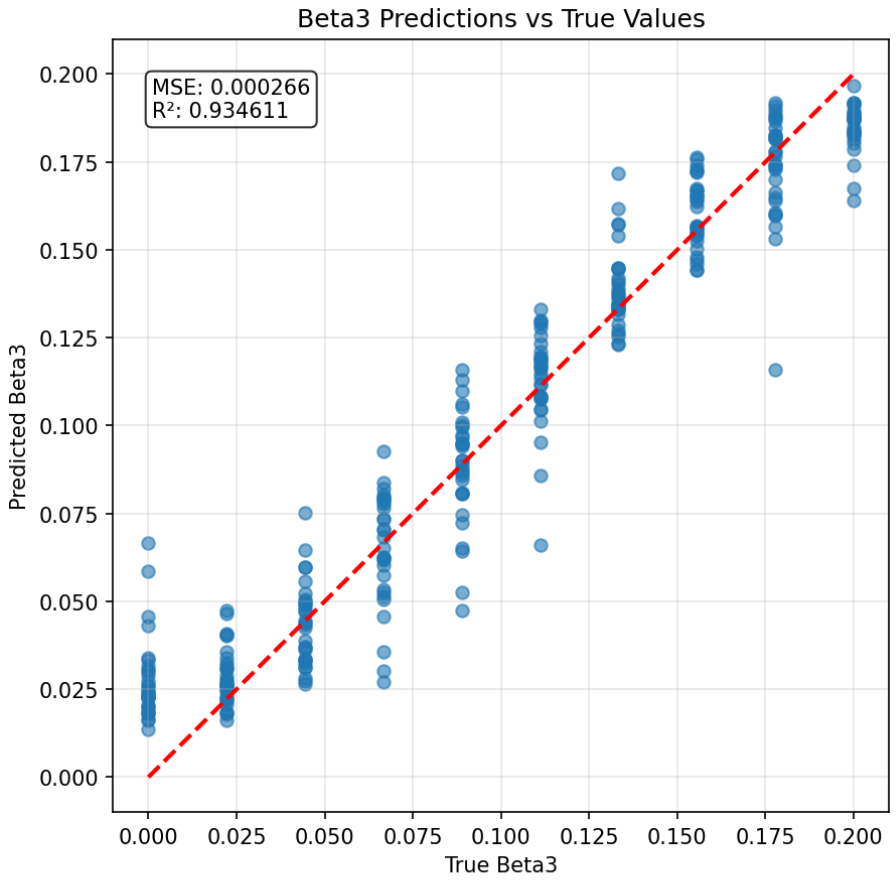
Feature Extraction: Efficiently captures global structures and local details.

Application: Used here as a regressor for β2 ,β3 and a classifier for Neutron Skin.

He K, et al. Deep residual learning for image recognition. 2016.

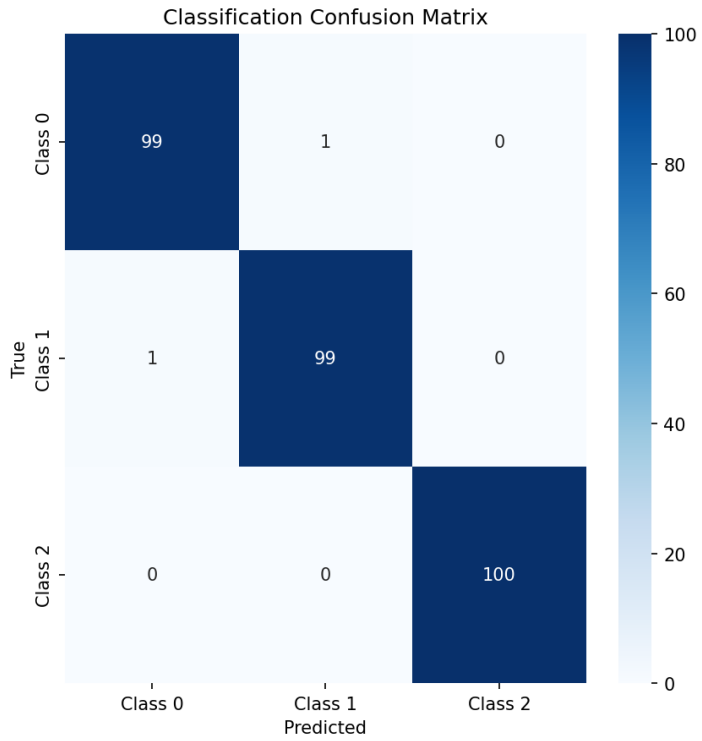
Model Performance: Prediction Accuracy of the ResNet Model





Predicted vs. True values for β_2 and β_3

R²≈95%



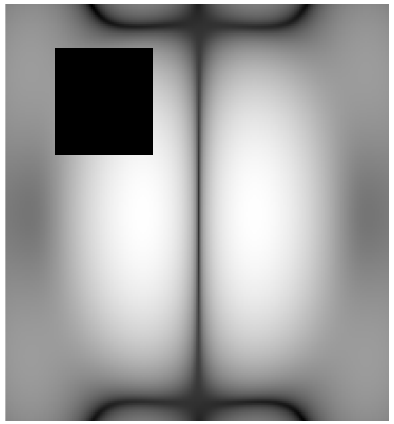
Neutron Skin classification.

Accuracy ≈ 99%

The model successfully handles multi-task learning, achieving high accuracy in simultaneously predicting deformation and neutron skin.

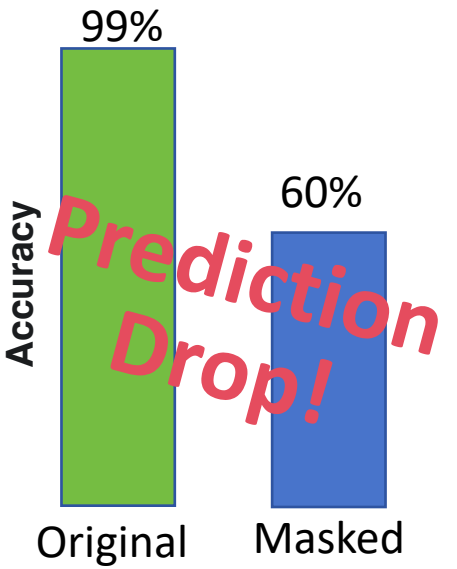
Interpretability Method: Prediction Difference Analysis (PDA)

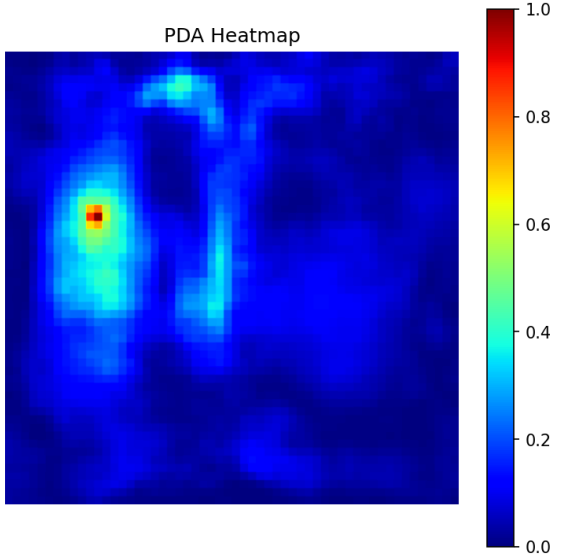
Input Image
(Original)



Masking
(Sliding Window)

ResNet

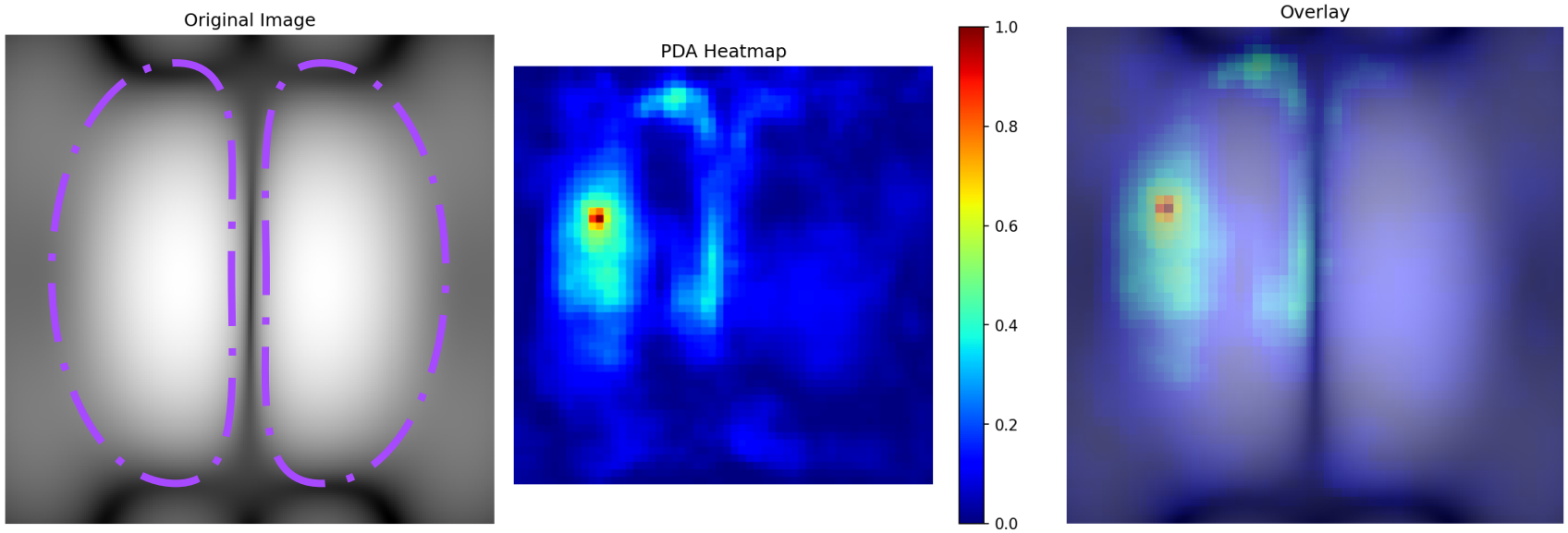




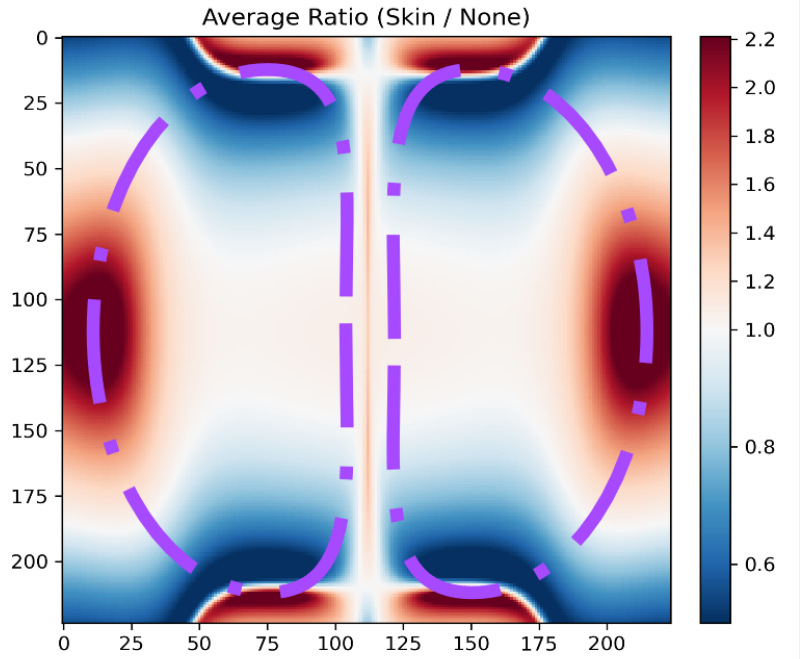
Zintgraf L M, et al. Visualizing deep neural network decisions: Prediction difference analysis. arXiv:1702.04595, 2017.

Interpretability Analysis: Neutron Skin Effect

Model Insight



Physics Verification

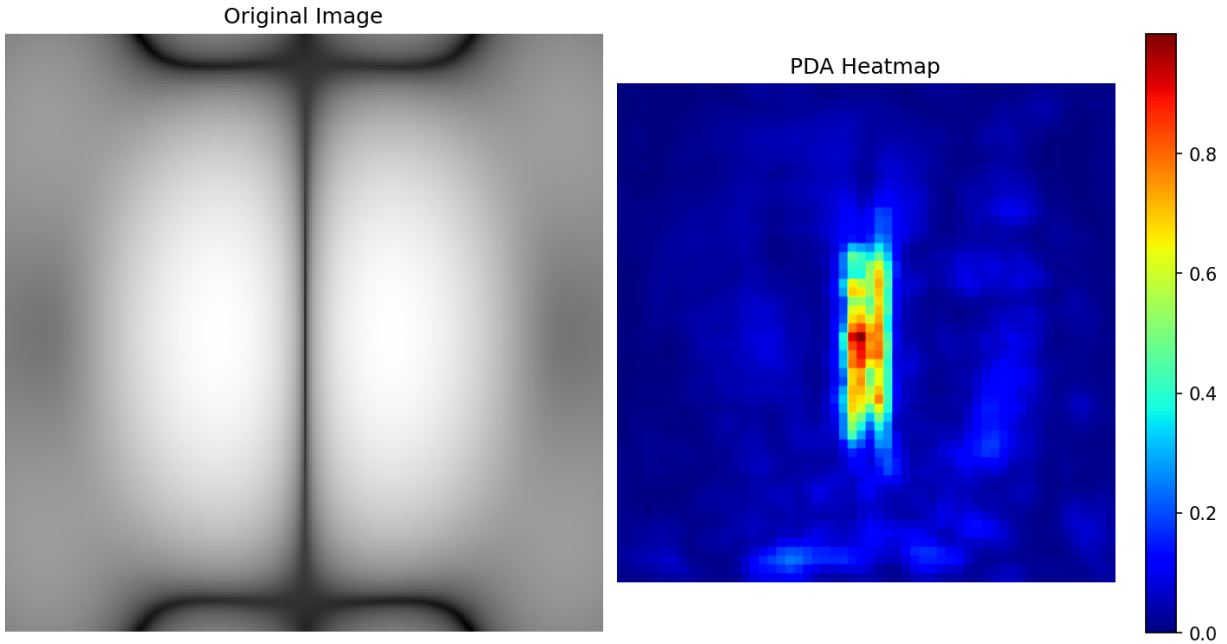


The Heatmap shows the network focuses on the edges of the Bright Spot, "the Butterfly Wings".

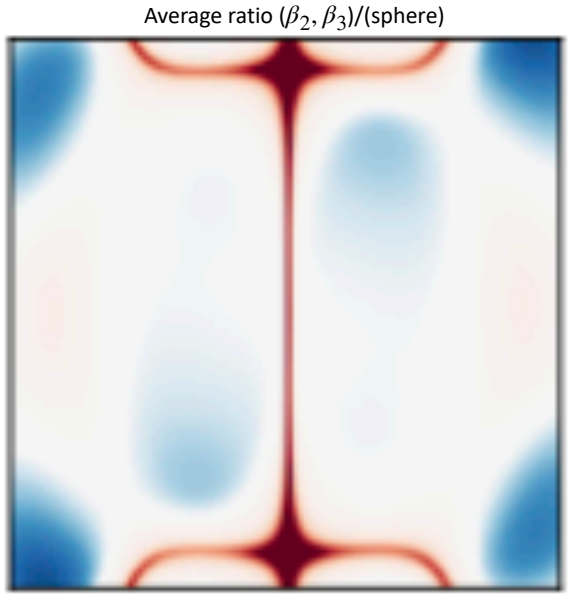
The Ratio Plot (Skin / No-Skin) confirms that physical differences occur exactly at the Bright Spot

Interpretability Analysis: Nuclear Deformation (β2,β3)

Model Insight



Physics Verification



PDA heatmap shows the network focuses on the interference dark fringes.

The Ratio Plot shows that deformation parameters primarily alter the dark fringes.

Physical Mechanism: Optical Analogy for Neutron Skin

$$\frac{d^2P}{dp_x dp_y} = \left| \mathcal{F}^{-1}\left\{ A_1(\vec{r} - \frac{\vec{b}}{2}) \right\} - \mathcal{F}^{-1}\left\{ A_2(\vec{r} + \frac{\vec{b}}{2}) \right\} \right|^2$$

$$= \left| \mathcal{F}^{-1}\left\{A_1(\vec{r})\right\} e^{i\vec{p}\cdot\frac{\vec{b}}{2}} - \mathcal{F}^{-1}\left\{A_2(\vec{r})\right\} e^{-i\vec{p}\cdot\frac{\vec{b}}{2}} \right|^2$$

Interference term
(Impact parameter b)

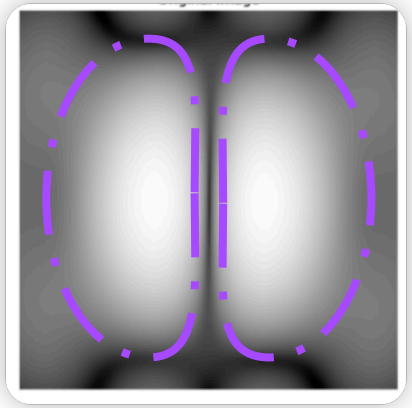
$$\vec{p}\cdot\vec{b} = 2n\pi$$

The two nuclei are an identical sphere: $A_1 = A_2 = A$

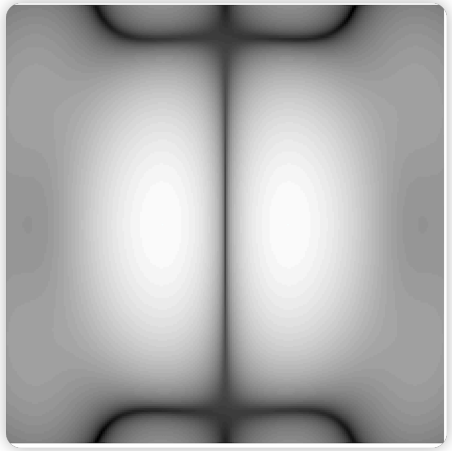
$$\frac{d^2P}{dp_x dp_y} = |\mathcal{F}^{-1}\{A(\vec{r})\}\ (e^{i\vec{p}\cdot\frac{\vec{b}}{2}} - e^{-i\vec{p}\cdot\frac{\vec{b}}{2}})|^2 = 4\,|\mathcal{F}^{-1}\{A(\vec{r})\}|^2 \sin^2(\vec{p}\cdot\frac{\vec{b}}{2})$$

Diffraction term
(Structure info)

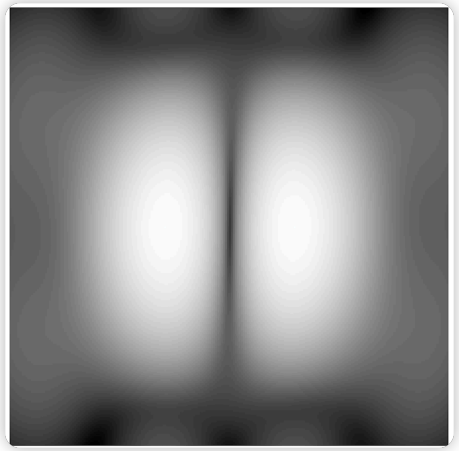
input example



Physical Mechanism: Optical Analogy for Nuclear Deformation



Small deformation: Sharp fringes



Large deformation: Smeared fringes
(Phase averaging effect)

$$\frac{d^2P}{dp_x dp_y} = \left| \mathcal{F}^{-1}\{A_1(\vec{r})\}e^{i\vec{p}\cdot\frac{\vec{b}}{2}} - \mathcal{F}^{-1}\{A_2(\vec{r})\}e^{-i\vec{p}\cdot\frac{\vec{b}}{2}} \right|^2$$

$$= F_1^2 + F_2^2 - F_1F_2^* e^{i\vec{p}\cdot\vec{b}} - F_1^* F_2 e^{-i\vec{p}\cdot\vec{b}}$$

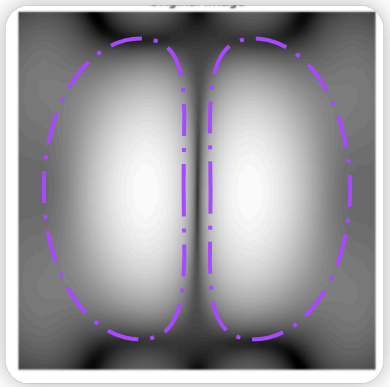
$$= F_1^2 + F_2^2 - |F_1F_2| \left(e^{i(\vec{p}\cdot\vec{b}+\Delta\phi)} + e^{-i(\vec{p}\cdot\vec{b}+\Delta\phi)} \right)$$

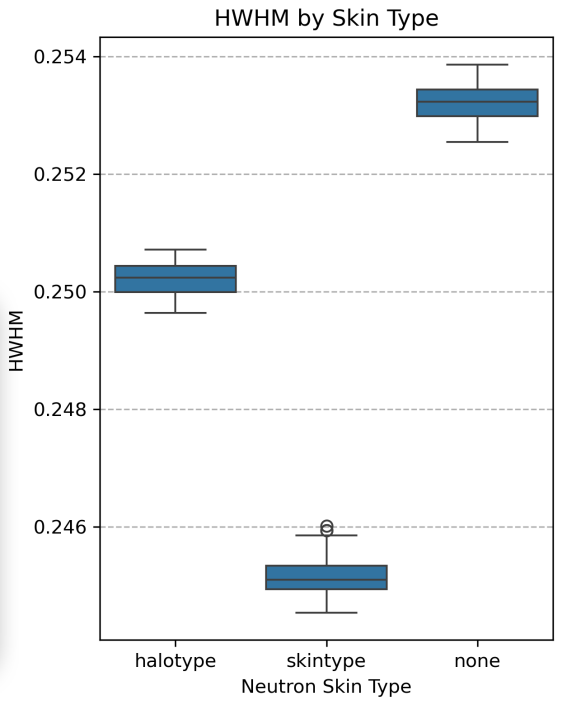
$$= F_1^2 + F_2^2 - 2|F_1F_2| cos(\vec{p}\cdot\vec{b} + \Delta\phi)$$

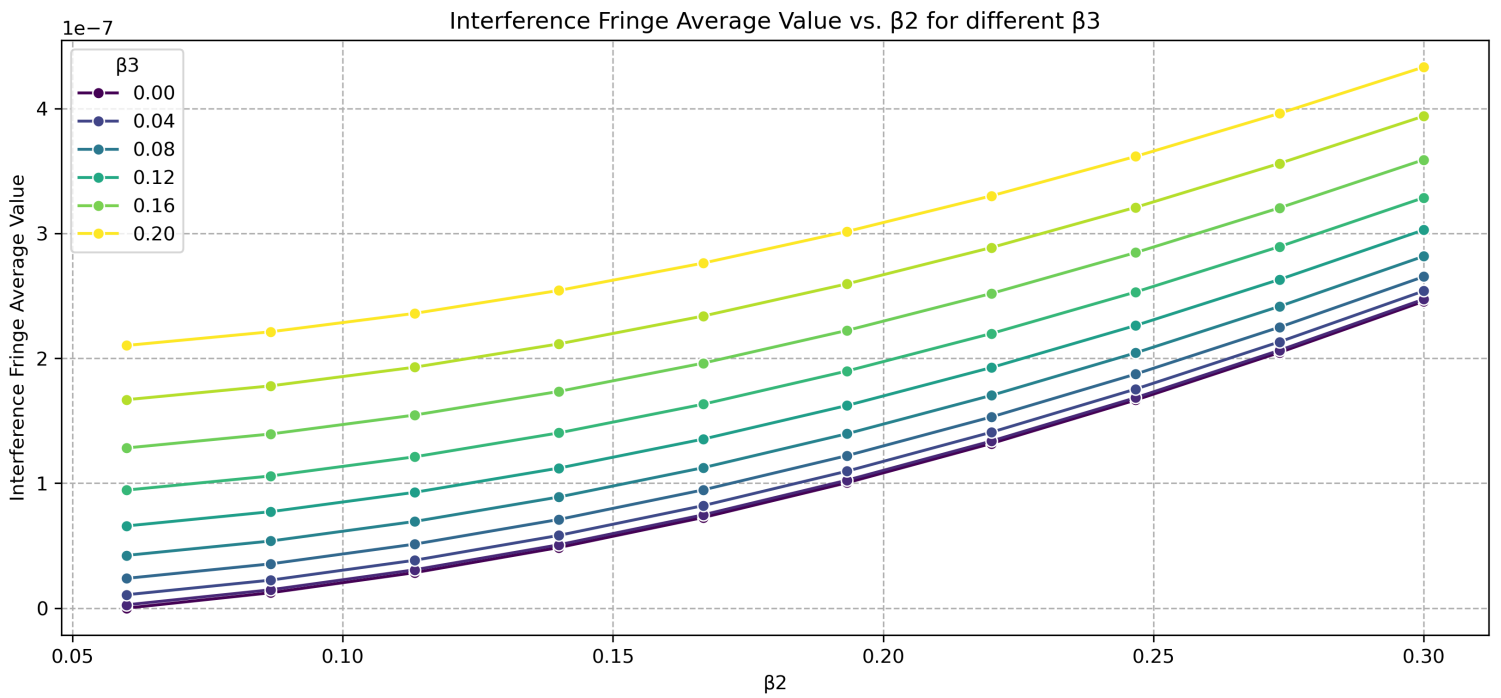
The location of the interference dark fringes shifts from $\vec{p}\cdot\vec{b} = 2n\pi$ in the spherical nucleus to $\vec{p}\cdot\vec{b} = 2n\pi - \Delta\phi$.

Proposed Observables Guided by Deep Learning

input example





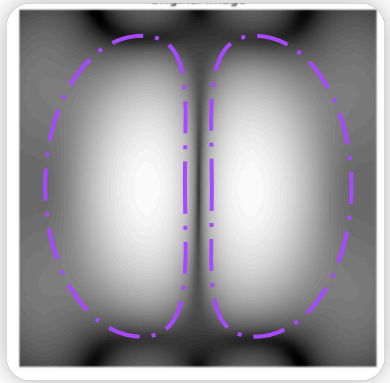


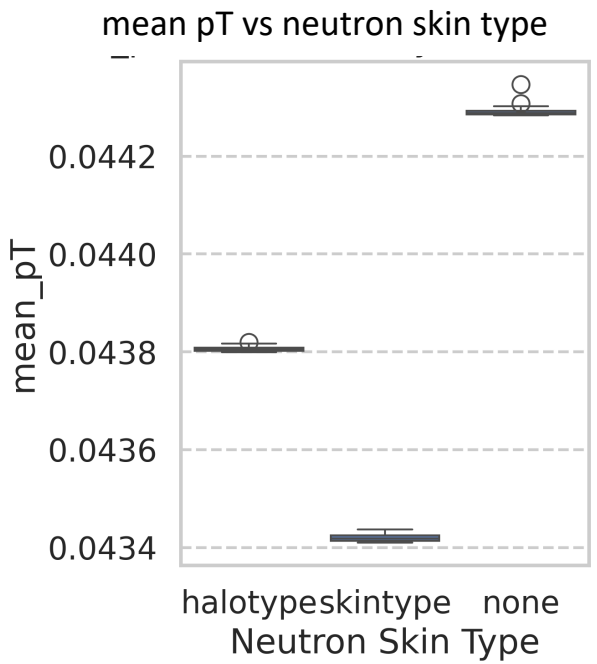
HWHM (Half-Width at Half-Maximum):
Definition: Area of intensity > Max/2.
Physical meaning: Reflects the size of the bright spot
(influenced by neutron skin).

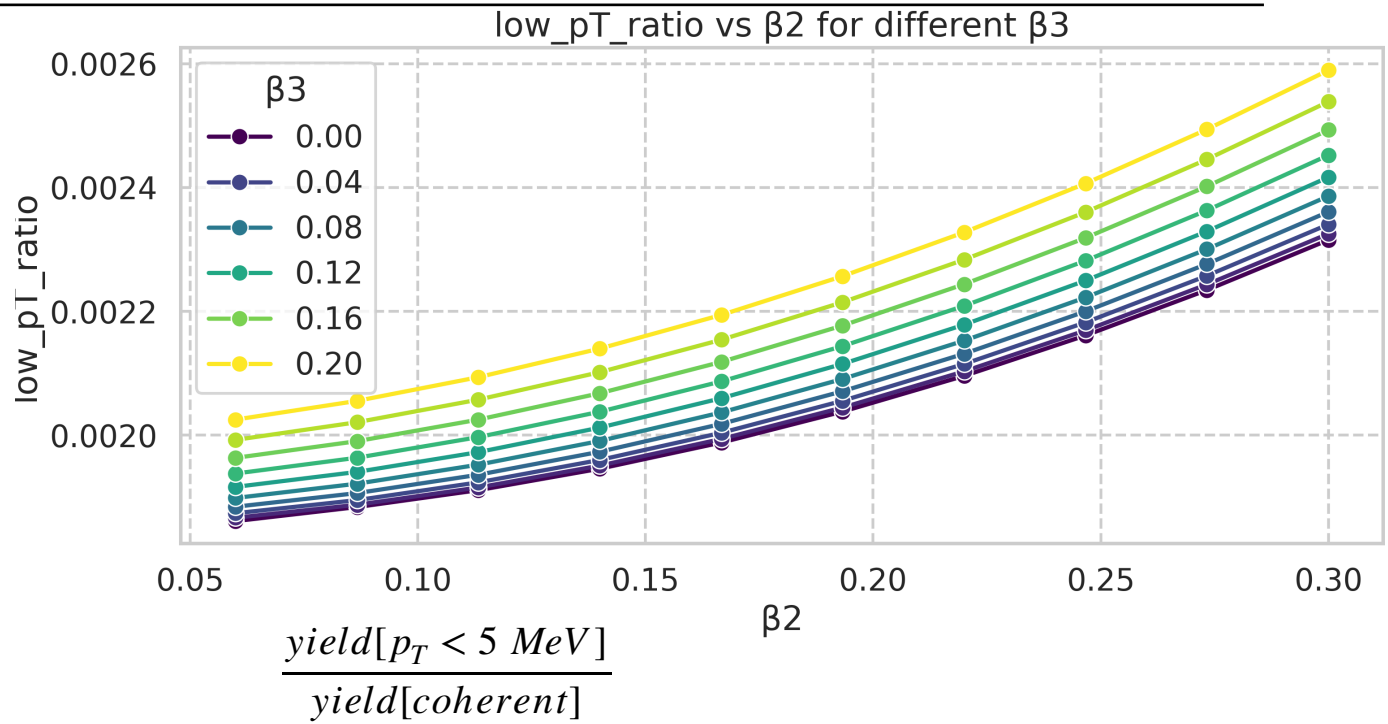
Average Intensity of Interference Fringes:
Definition: Average value of the lowest 5% intensity pixels.
Physical meaning: Reflects the "depth" of dark fringe
(influenced by deformation).

Connection to Traditional Observables： mean pT and low pT ratio

input example







$$\frac{yield[p_T < 5\ MeV]}{yield[coherent]}$$

HWHM ⇒ Mean p_T

A larger HWHM (broader central spot) → momentum distribution extends to higher p_T

Result: larger HWHM to higher mean p_T

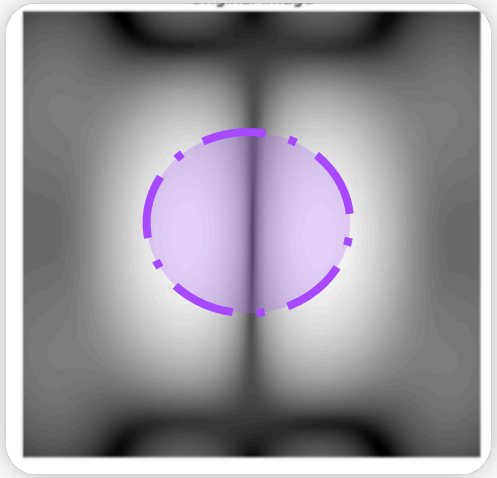
Fringe Intensity ⇒ Low p_T Ratio & v_n

Fringe Intensity measures the "depth" and the clarity of interference minima.

Result: lower Fringe Intensity → low p_T yield in the dark fringe region

or → azimuthal anisotropy (v_2, v_3) caused by fringe smearing (detailed in the next slides).

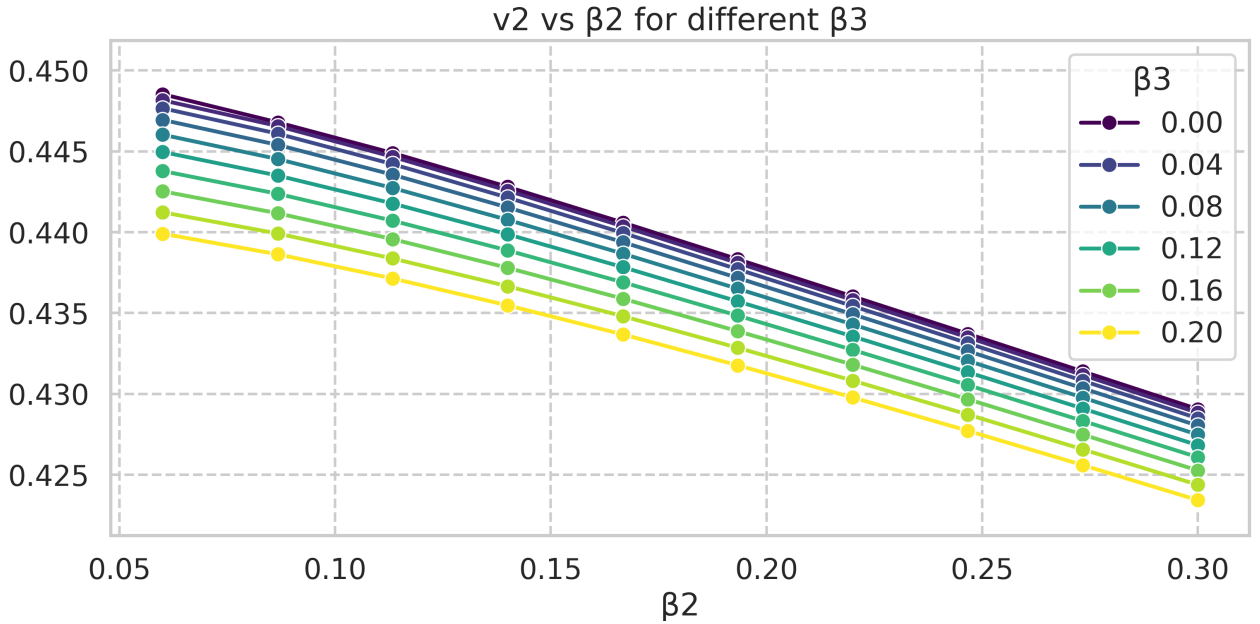
Low pT Region Analysis: v2 v3

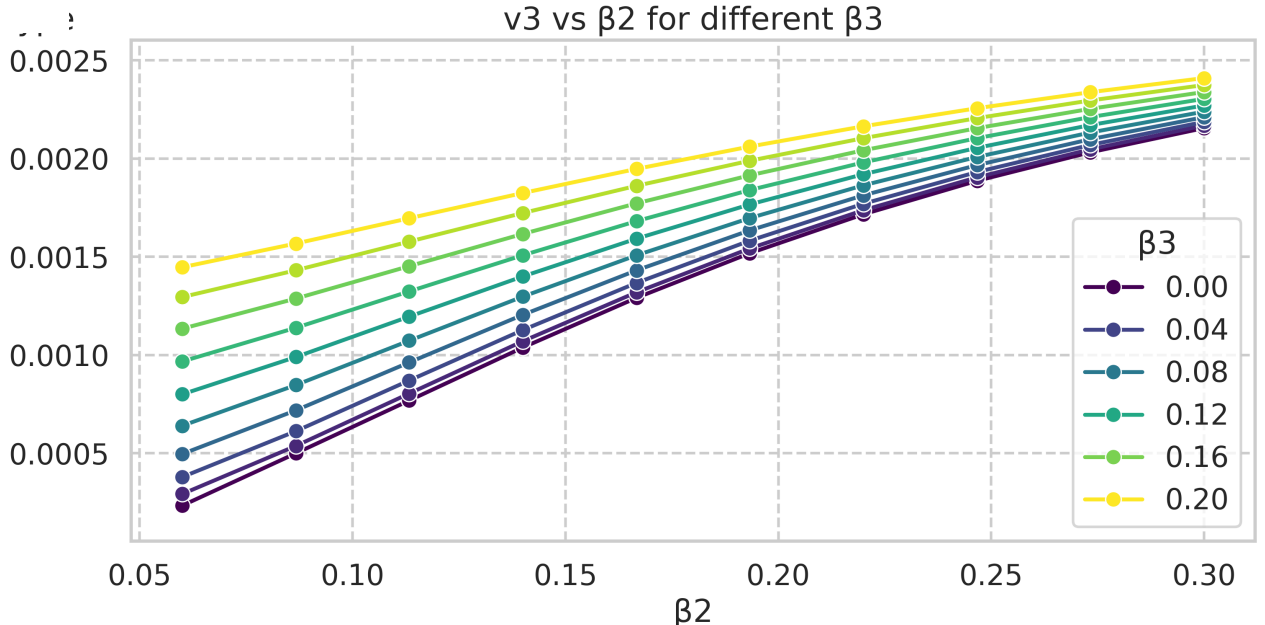


pt<0.05GeV

$$v_2 = \langle cos(2\phi) \rangle$$

$$v_3 = \langle cos(3\phi) \rangle$$

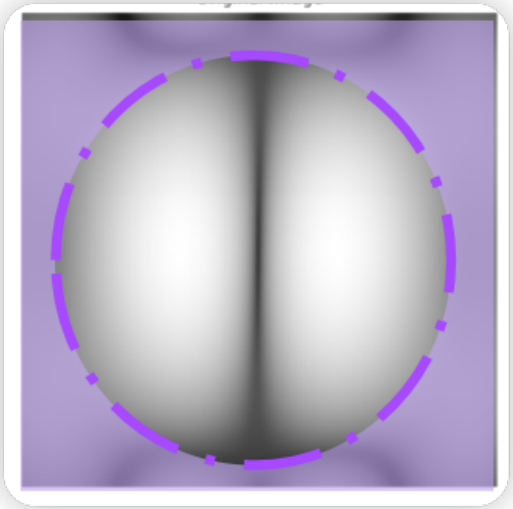




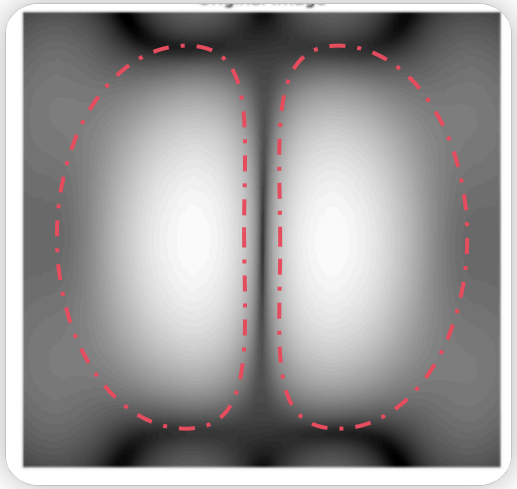
This region is characterized by smeared dark fringes .

Low pT flow harmonics serve as sensitive probes for deformation parameters.

High pT Region Analysis: v2 v3



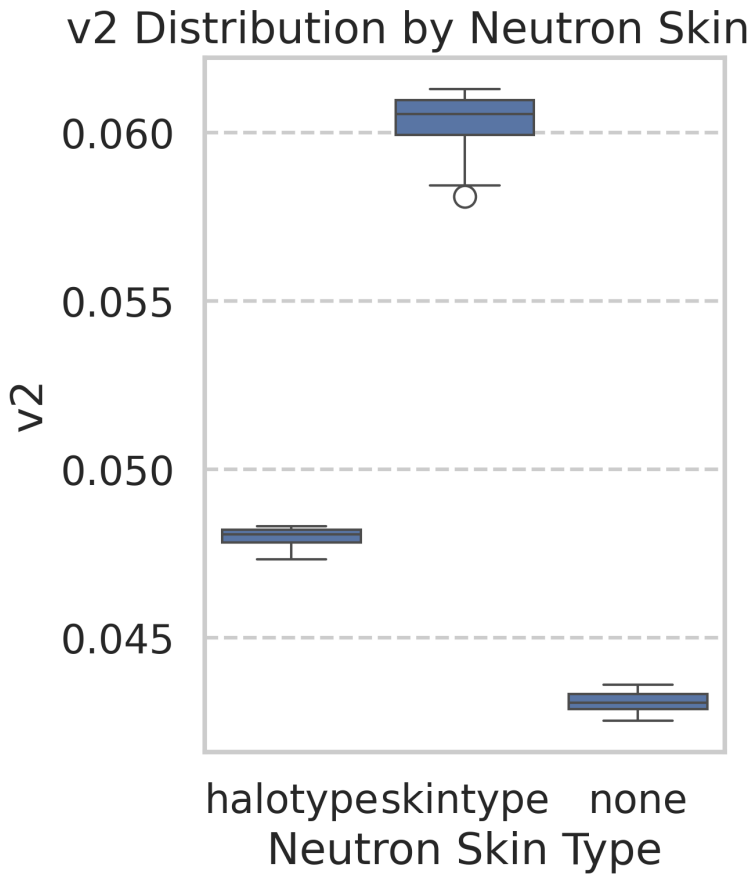
0.14GeV<pt<0.16GeV

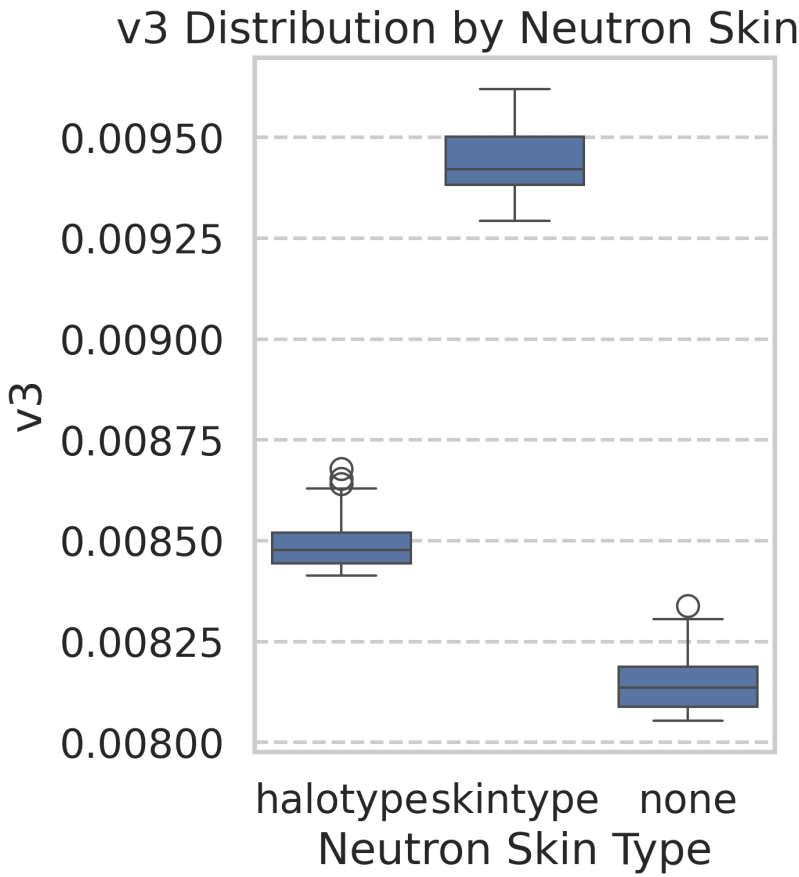


Butterfly shaped region affected by neutron skin

$$v_2 = \langle cos(2\phi) \rangle$$

$$v_3 = \langle cos(3\phi) \rangle$$





Neutron skin affects the butterfly shaped region and thus the v2 v3 in this high pT region.

Summary

- Methodology: Successfully applied Multi-Task Deep Learning to extract nuclear structure (β2,β3, Skin) from UPC J/ψ distributions.

- Interpretability: A systematic analysis revealed that the model relies on the Butterfly Wings (for Skin) and interference fringe (for Deformation).

- Observables: Defined (mean p_T, low p_T ratio, v_2, v_3) as practical experimental observables, bridging the gap between deep learning "Black box" and physical measurement.

- Outlook: Future work will include incoherent noise to test robustness and application to real experimental data.