



# FractionalNets - A Neural Network for Approximating Fractional Derivatives

Michigan Tech

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## INTRODUCTION

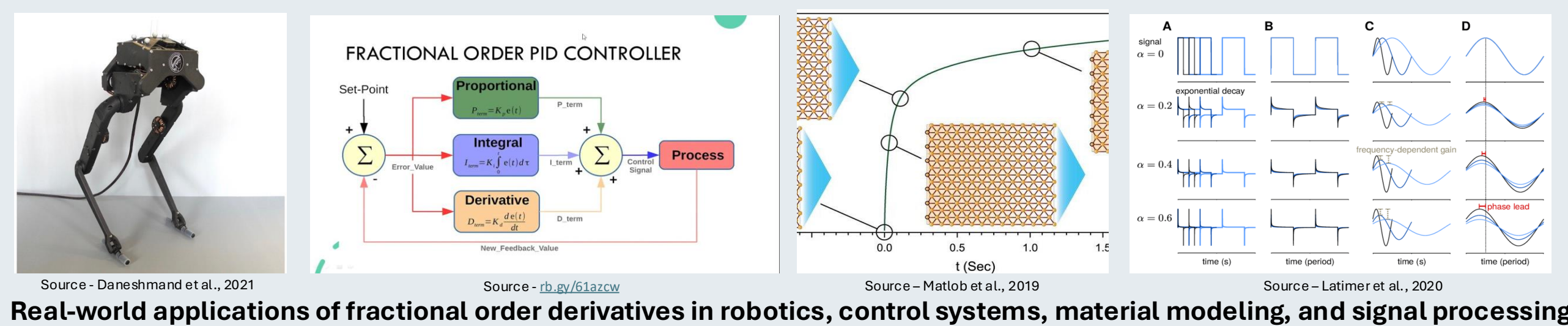
- What are Fractional derivatives(FD)?
  - Derivative for any arbitrary non-integer order (i.e 0.5, 0.25)
  - Do not have a simple interpretation like integer-order derivatives.
  - Fractional derivatives measure memory effects – Past values influence present derivatives (Difficult to interpret)
- How do we calculate FD?
  - Notably **Riemann-Liouville (RL)** and **Caputo definition**
- Fixed-formula FD computation limits accuracy and adaptability.
- Why are FDs important –
  - FDs accurately describe memory effects in materials and fluid dynamics improving predictive models.
  - Used in robotics and circuit design for better stability, noise reduction, and adaptive control in engineering applications.

$$D_a^\alpha(f)(t) = \frac{1}{\Gamma(n-\alpha)} \frac{d^n}{dt^n} \int_0^t \frac{f(x)}{(t-x)^{\alpha-n+1}} dx$$

Riemann-Liouville

$$D_a^\alpha(f)(t) = \frac{1}{\Gamma(n-\alpha)} \int_0^t \frac{f^{(n)}(x)}{(t-x)^{\alpha-n+1}} dx$$

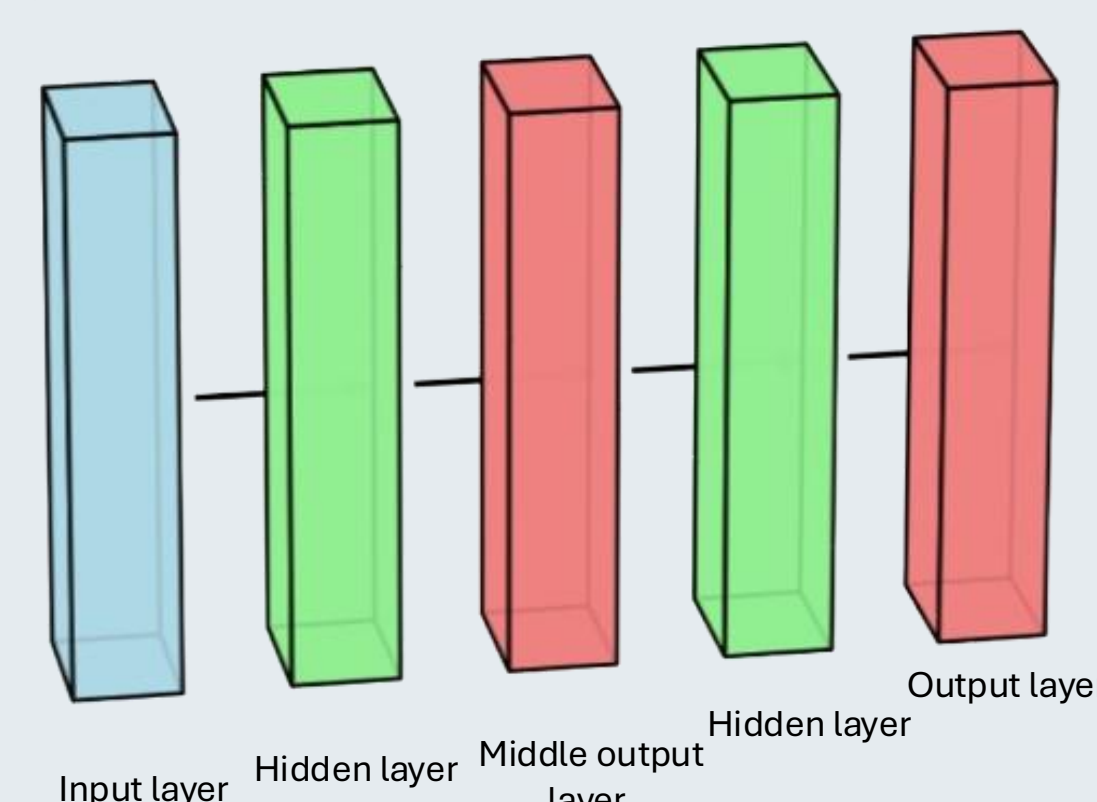
Caputo



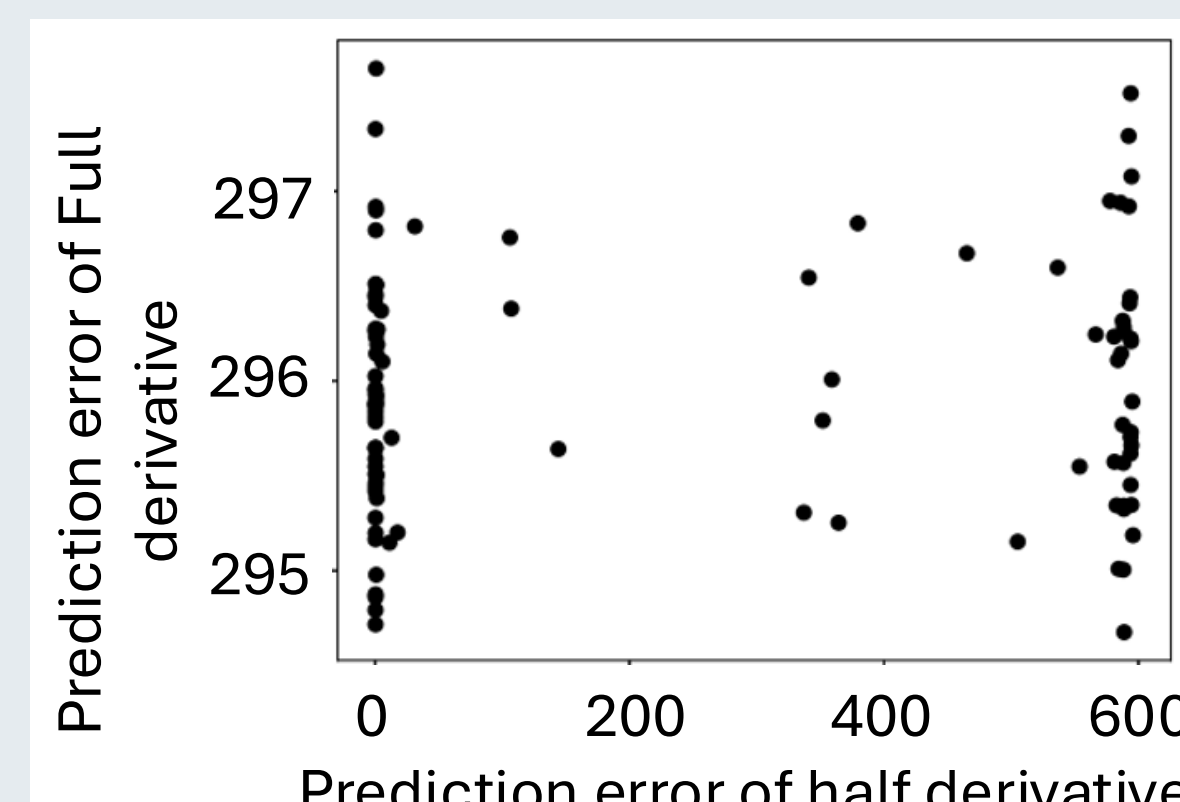
Real-world applications of fractional order derivatives in robotics, control systems, material modeling, and signal processing.

## RELATED WORK

- Existing Method - A Symmetric Neural Network to Compute Fractional Derivatives by Training with Integer Derivatives[1]
  - A symmetric neural network was trained using integer derivatives only.
  - The middle layer learns the half-derivative implicitly.
  - The middle layer in the network acts as an interpolator in the derivative space, naturally approximating the half-order derivative by learning the transition between integer derivatives.



Model structure

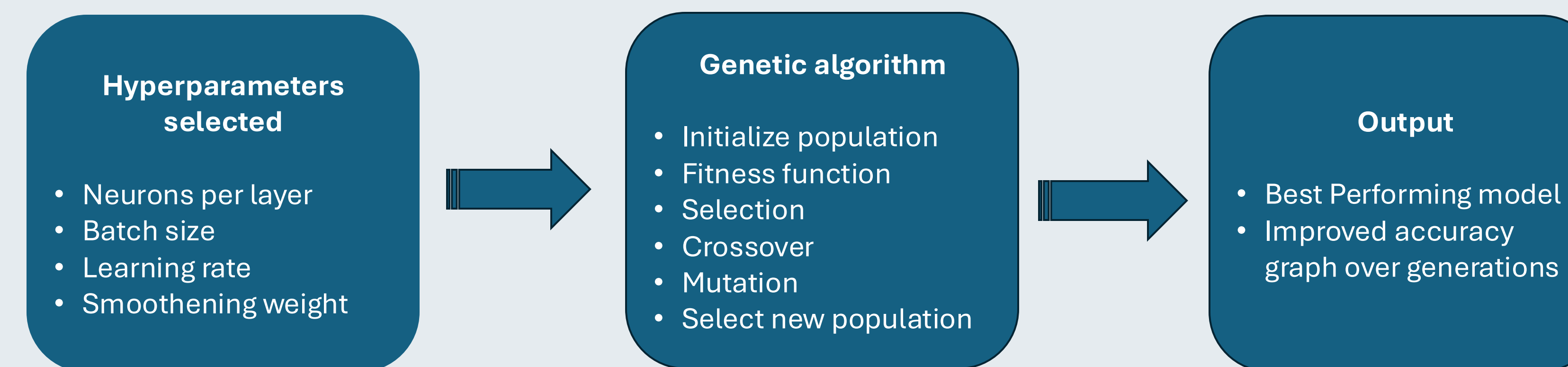


Models' performance

- Limitations:**
  - Only **80% accuracy** on polynomials.
  - Fixed hyperparameters – **not optimized**.
  - The **effect of weight initialization** was **not studied**.

## PROPOSAL

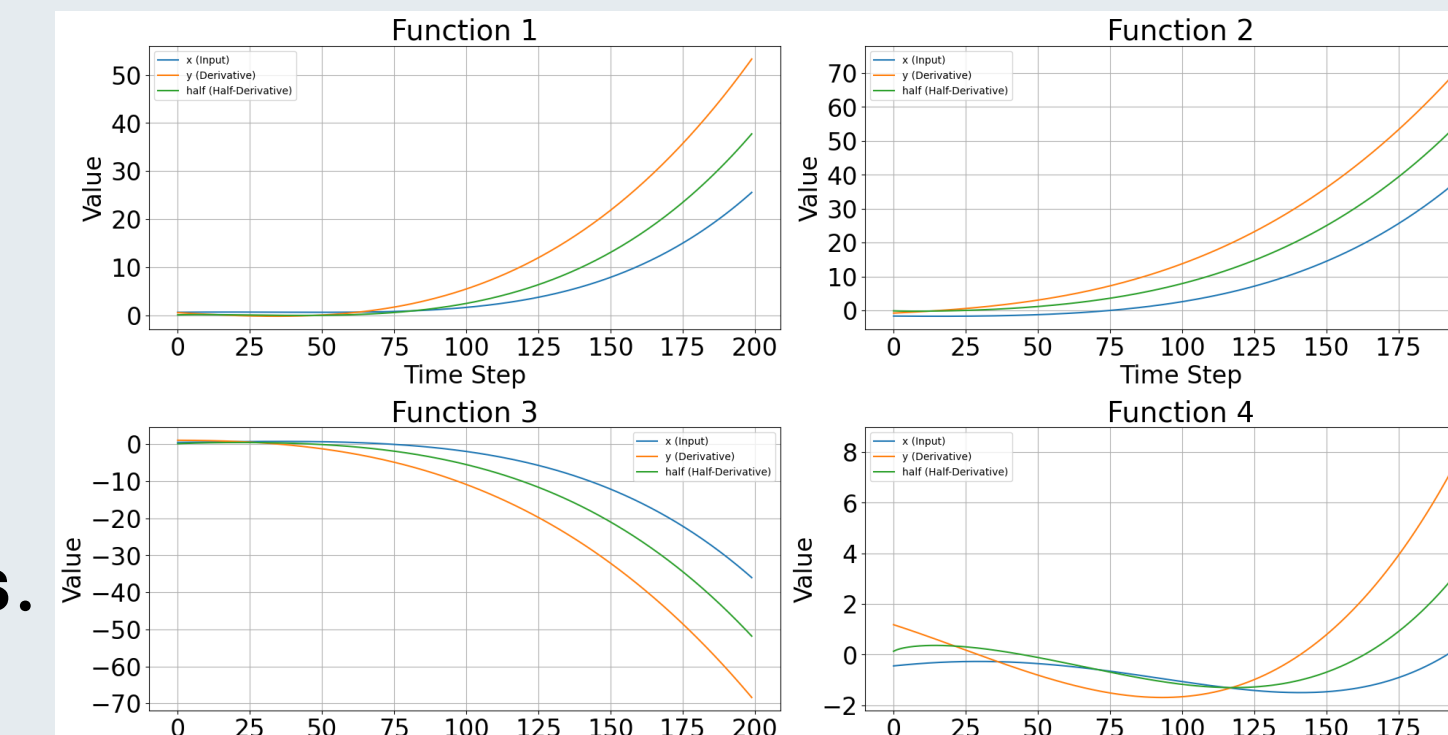
- Goal for FractionalNets –
  - Improve FD prediction beyond 80%** using **Genetic Algorithms (GA)** and **Weight Initialization**.
  - Optimize hyperparameters dynamically** instead of using fixed values.



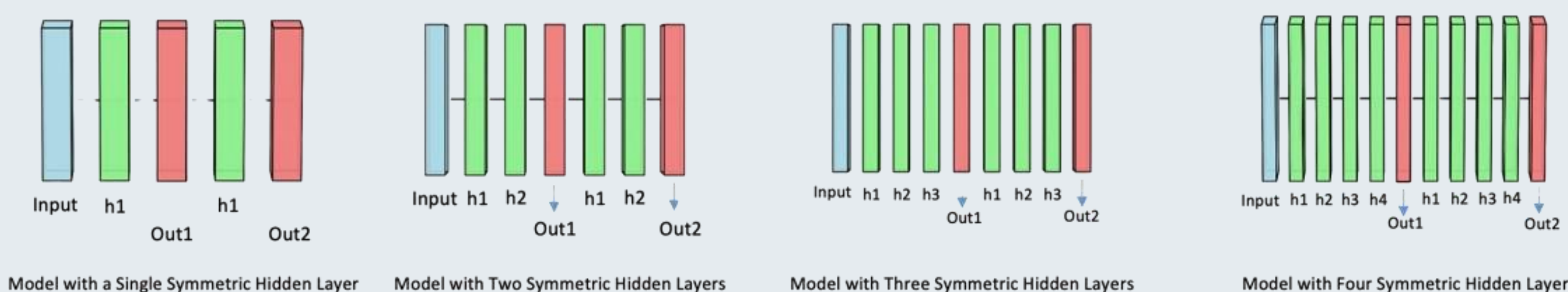
- Key Assumptions –
  - Hyperparameter Dependence:** Model performance depends on **optimized hyperparameters via GA**.
  - Weight Initialization Dependence:** Performance improves with **better initial weight selection**.

## METHODOLOGY

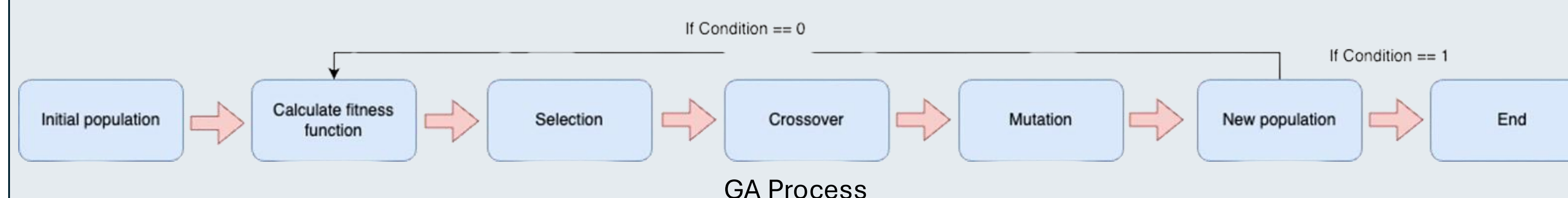
- Data Generation–**
  - 10,000 polynomials** generated.
  - Random coefficients in **[-2,2]**, Order = 4.
- Model Architecture –**
  - Tested **1, 2, 3, and 4 symmetric hidden layers**.
  - Middle layer represents the half-derivative**



Polynomial data



- Genetic Algorithm (GA) for Hyperparameter Optimization –**
  - Genetic Algorithm is an optimization technique inspired by **natural selection**.
  - It iteratively evolves solutions to find the best one over multiple generations.

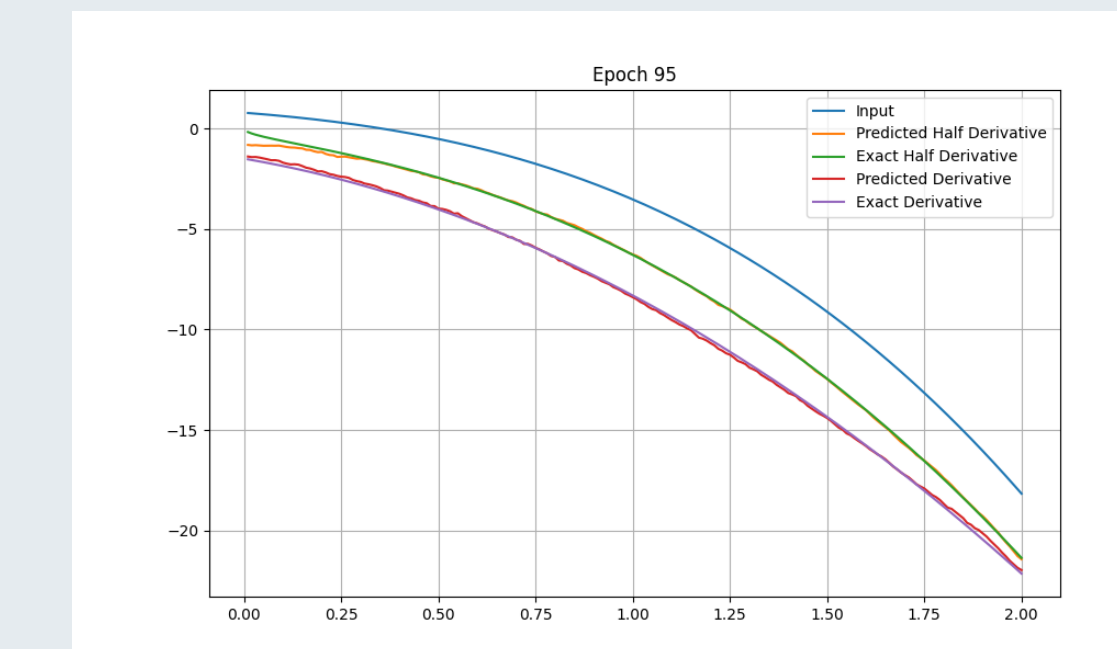


GA Process

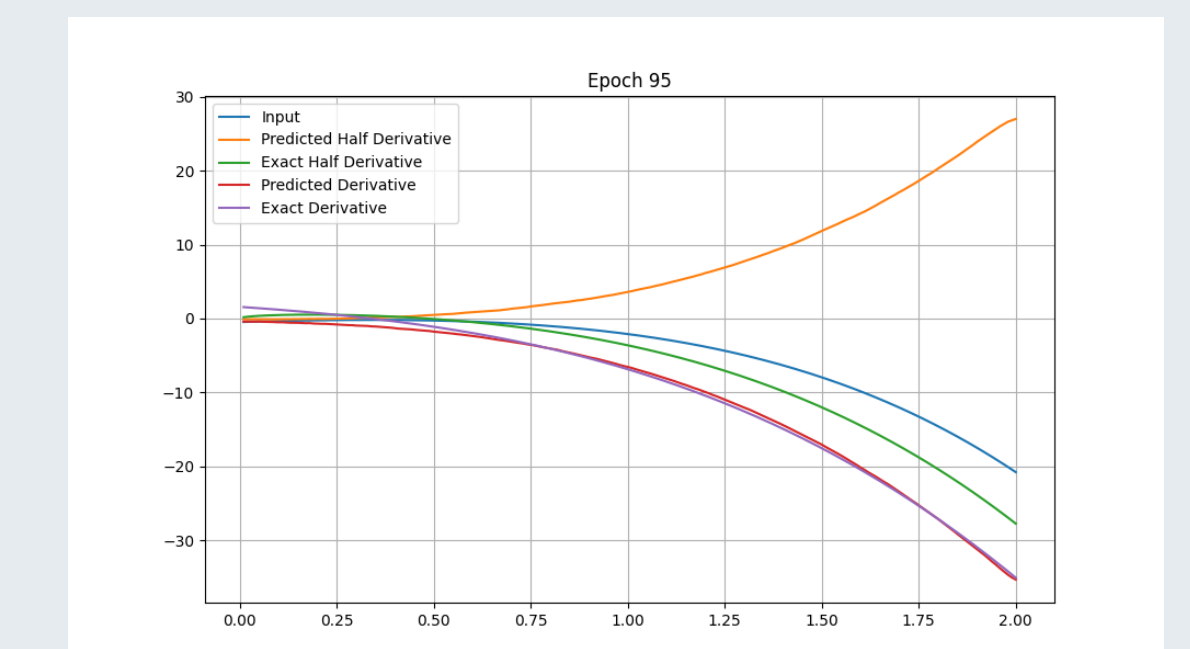
[1] Chen, T., & Goodwine, B. (2022, January). A symmetric neural network to compute fractional derivatives by training with integer derivatives. In *2022 IEEE/SICE International Symposium on System Integration (SII)* (pp. 291-296). IEEE.  
[2] Daneshmand, E., Khadiv, M., Grimminger, F., & Righetti, L. (2021). Variable horizon mpc with swing foot dynamics for bipedal walking control. *IEEE Robotics and Automation Letters*, 6(2), 2349-2356.  
[3] Images from - <https://www.youtube.com/watch?v=UzmGvASK7Zw>  
[4] Latimer, K. W., & Fairhall, A. L. (2020). Capturing multiple timescales of adaptation to second-order statistics with generalized linear models: gain scaling and fractional differentiation. *Frontiers in systems neuroscience*, 14, 60.  
[5] Matlob, M. A., & Jamali, Y. (2019). The concepts and applications of fractional order differential calculus in modeling of viscoelastic systems: A primer. *Critical Reviews™ in Biomedical Engineering*, 47(4).

## DISCUSSIONS & RESULTS

- Inverse FD Predictions Are Valid –
  - Some polynomials **have valid inverse half-derivatives**. **Applying the inverse still results in the correct first derivative**.



Direct Prediction

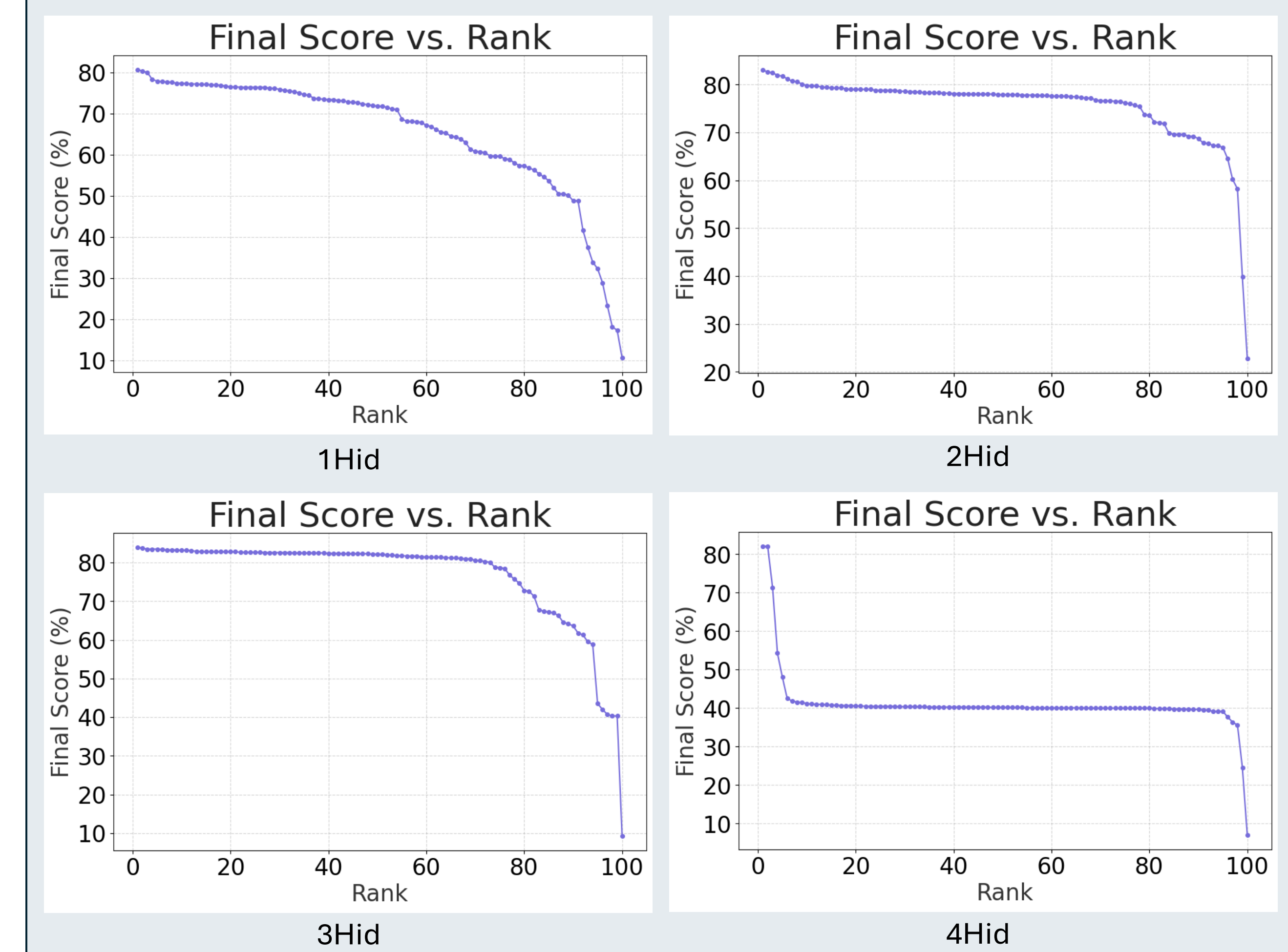


Inverted Prediction

- Calculation Metrics – **Final Score**
  - We define accuracy based on how well the predicted half-derivative matches the actual one using AUC error ratios.

$$\text{Error Ratio} = \frac{\text{Selected AUC}}{\text{Total Area of Actual Half-Derivative}}$$

- Genetic Algorithm Optimization –
  - Ran **100 generations** of different models.
  - Found that **3 Hidden Layers (400, 600, 800 neurons)** consistently performed best.



## Weight Initialization and Future work

PyTorch defaults to Kaiming He Uniform Initialization. Testing Kaiming Normal, Xavier Glorot, and Orthogonal Initialization to push FD approximation accuracy beyond 80% using neural networks + Gas

### Future work –

- Expand dataset: sinusoids, exponentials functions.
- Investigate finer fractional derivatives: **0.25, 0.1**.
- Develop an **API for FD computation** for broader accessibility.