Evolutionary Exploration of a Neural Network for Predicting Ultrasound Propagation

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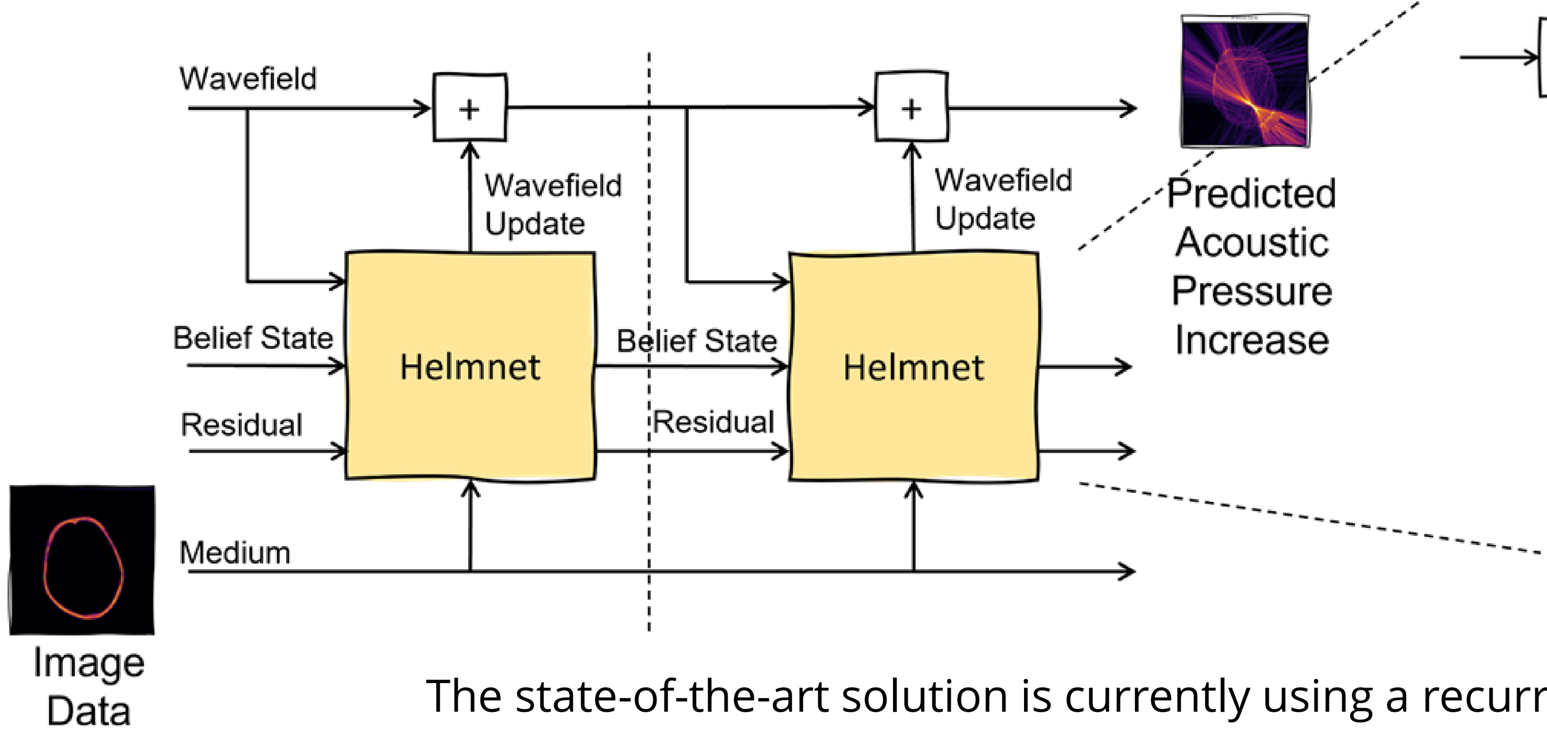
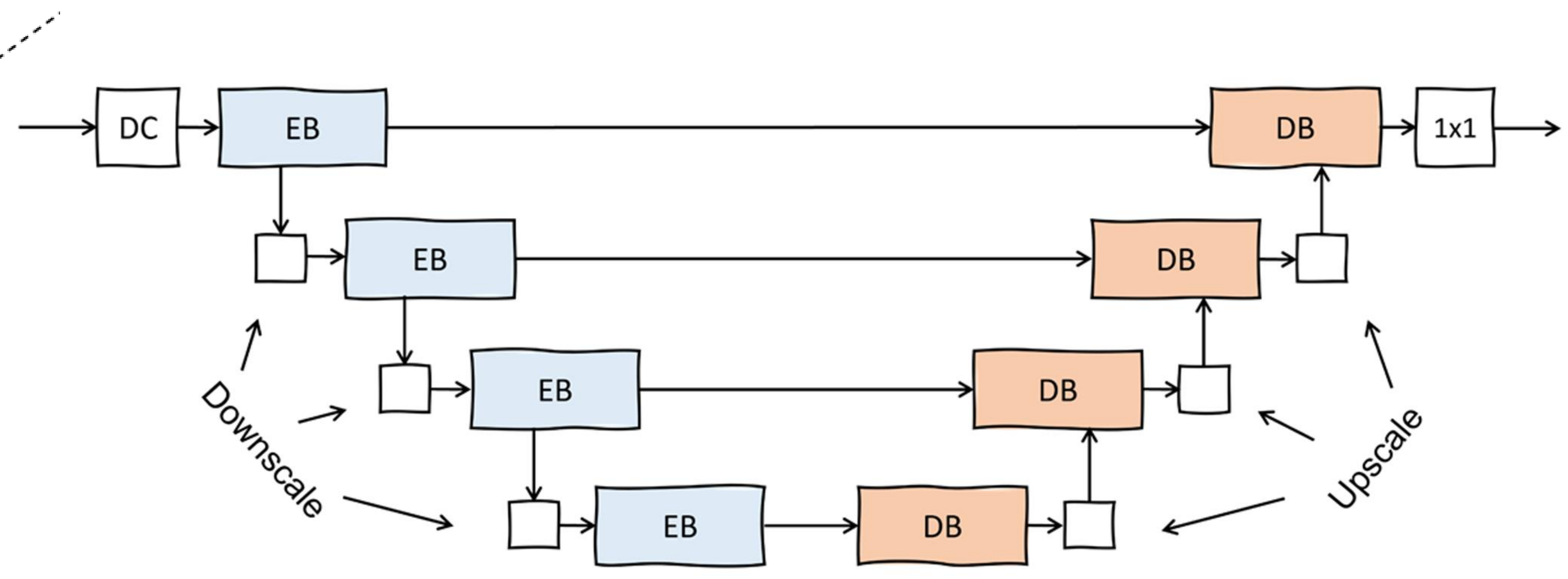
1 Introduction

The search for the optimal treatment plan in a focused ultrasound-based procedure is a complex multi-modal problem. It aims to deliver a solution within a clinically relevant time frame while maintaining precision above a critical threshold. We must balance clinical speed with precision. Machine learning offers a promising solution, as a recent neural predictor for acoustic skull propagation speeds up simulations significantly. To delve deeper into the design, we attempted to improve the solver using an evolutionary algorithm, questioning the significance of different building blocks. By utilizing Genetic Programming, we significantly enhanced the solution, resulting in a solver with approximately an order of magnitude better Root Mean Square Error (RMSE) for the predictor, all while delivering solutions within a reasonable time frame. Additionally, a second study explored the impact of multi-resolution encoding on network precision, offering insights for further research on memory blocks and convolution kernel sizes in Partial Differential Equation (PDE) Recurrent Convolutional Neural Network (RCNN) solvers.

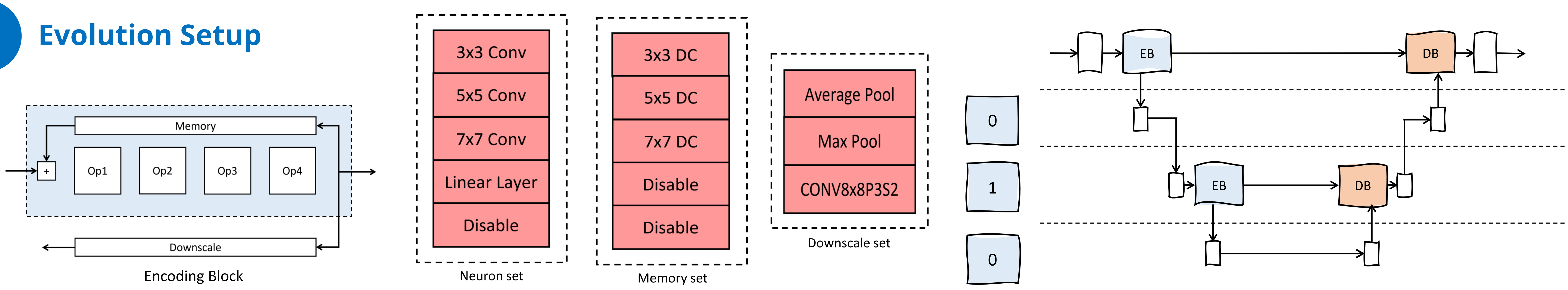
2 Base Architecture

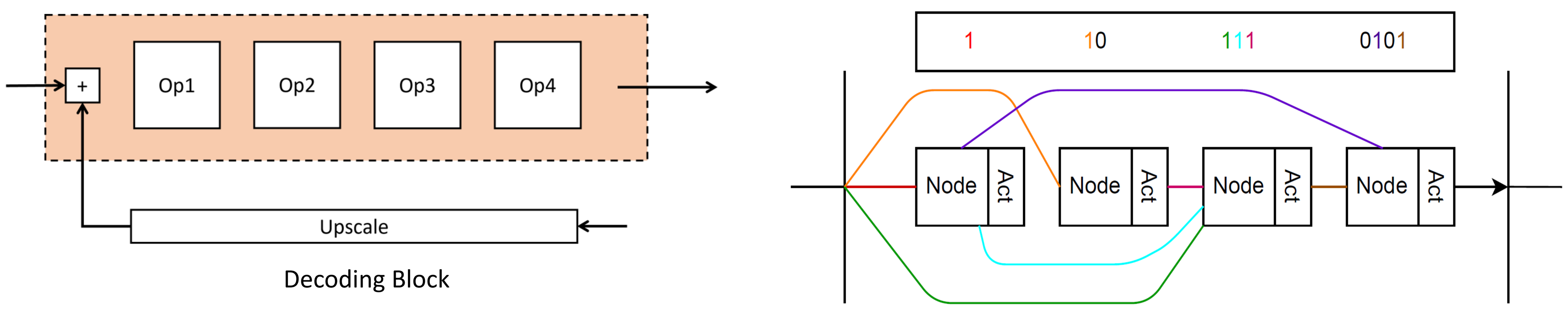




The state-of-the-art solution is currently using a recurrent UNet architecture, 47k parameters and achieving precision in order of 10^{-5}.

3 Evolution Setup



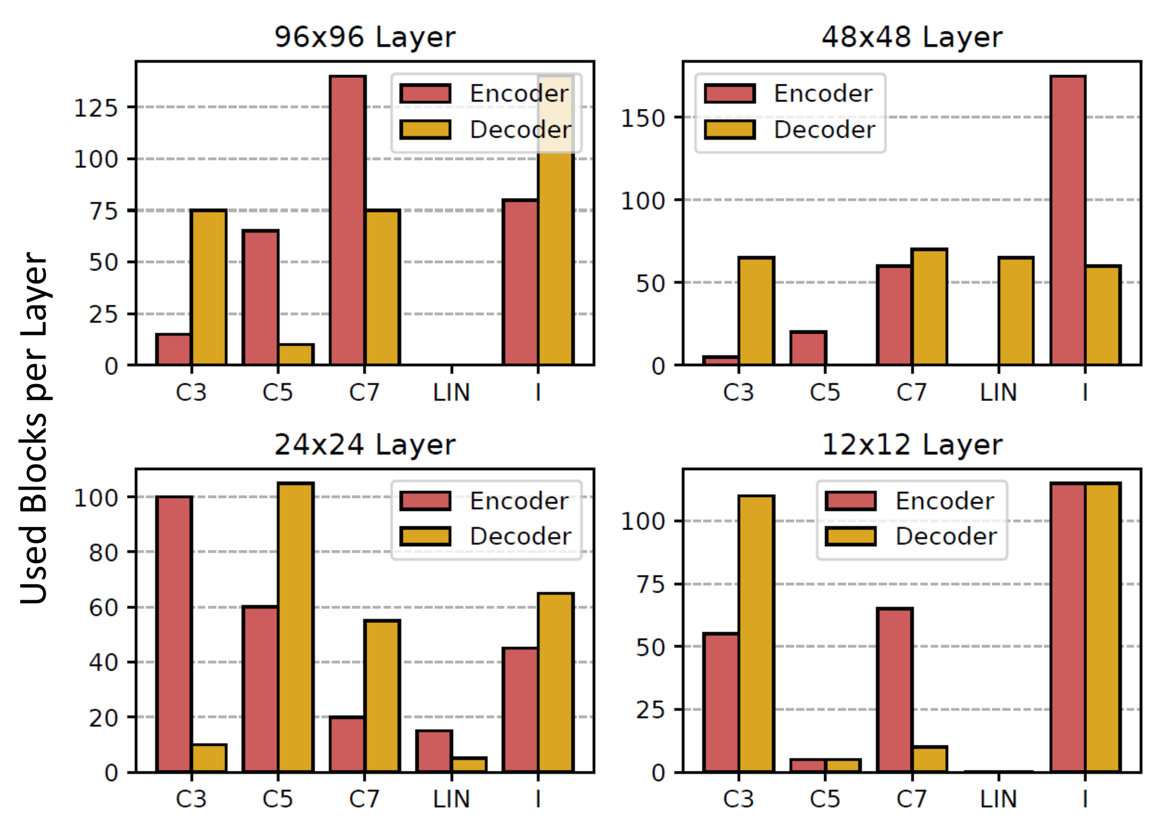


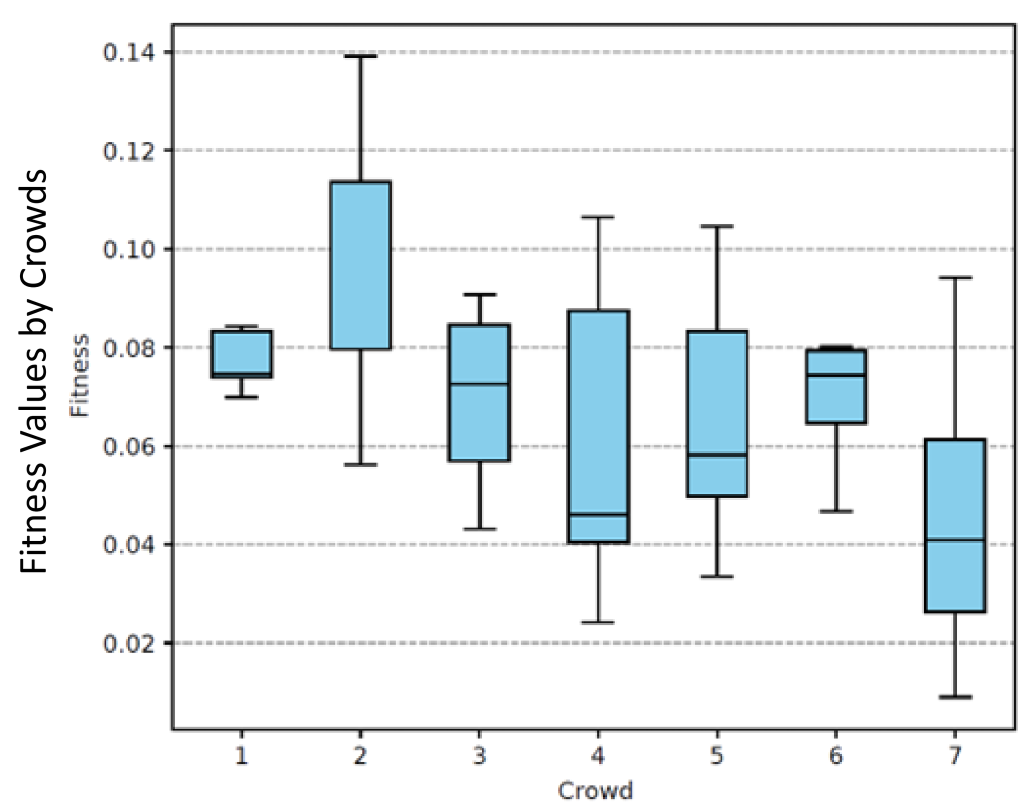
Each resolution layer is assigned a bit, expressing whether this resolution layer is enabled. For this purpose, a crowding idea is introduced to separate solutions based on the enabled and disabled resolution layers.

4 Preliminary Results

SA-Assisted - exploration of different crowds.

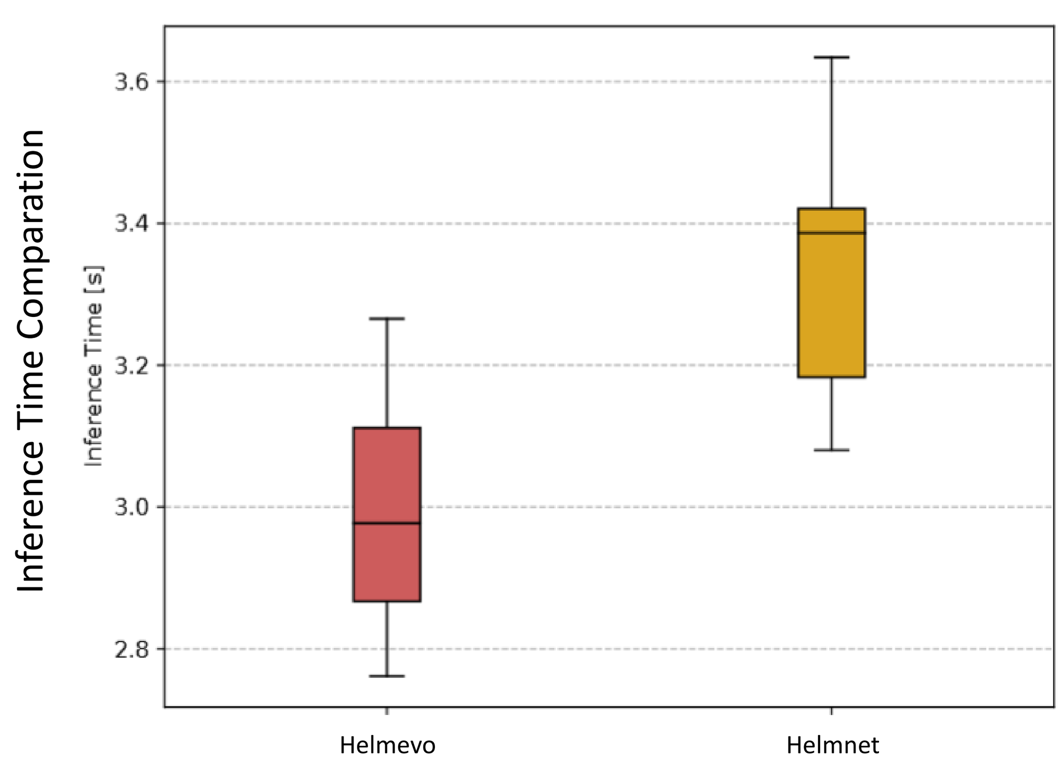
- (8, 64) scheme, each crowd creates its own subpopulation.
- 20 generations.
- Training 20 epochs, 250 iteration per sample.
- Crowds split ratio is optimized by a cooperating Simulated Annealing algorithm with linear cooling.
- Up to one full block is changed to generate an offspring.

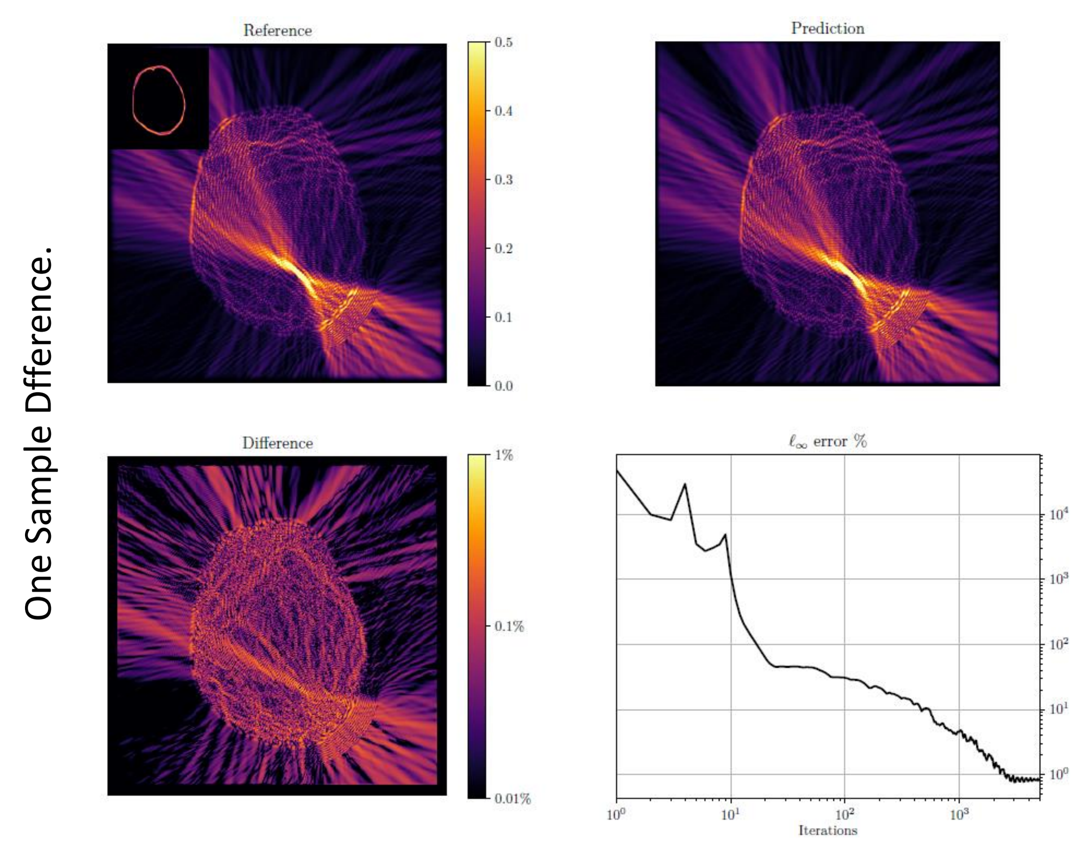




Evo Adaptation - optimize the current architecture and promote exploitation.

- (1 + 15) scheme
- 20 generations.
- Training 20 epochs, 250 iteration per sample.
- Two mutation rates are used:
  - Up to one full block is changed to generate an offspring.
  - 10% of the offspring can change their crowd.





k-Wave A MATLAB toolbox for the time-domain simulation of acoustic wave fields

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