PREDICTING BUBBLE DYNAMICS WITH DEEP LEARNING

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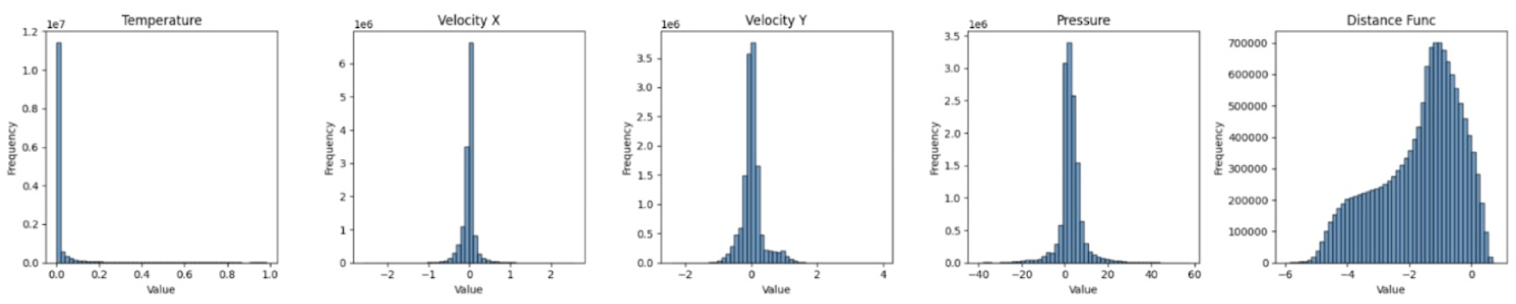
MOTIVATION

Boiling is a complex phase-change phenomenon essential for applications like electronics cooling, nuclear energy, and desalination. However, modeling boiling bubbles is challenging due to multiphysics interactions, including phase transitions, fluid dynamics, and heat transfer. Traditional CFD simulations are costly and hard to scale. BubbleML, a high-resolution dataset from Flash-X simulations, enables ML models to efficiently learn and predict bubble dynamics. By leveraging data-driven approaches, we aim to bridge the gap between physical simulations and forecasting, making bubble behavior prediction more accessible and cost-effective.

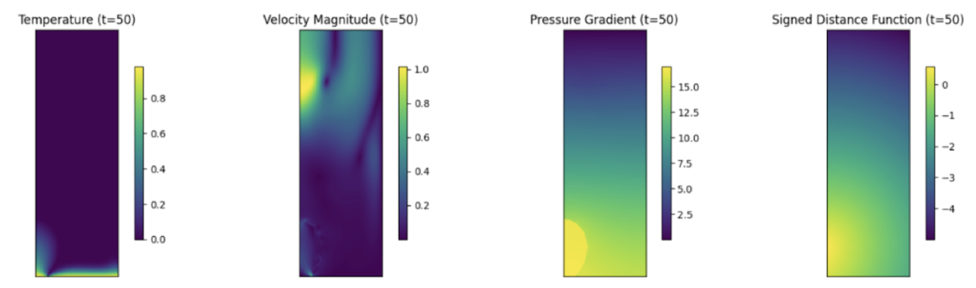
DATASET

BubbleML contains 500 timesteps of labeled data with a spatial resolution of 288 $\times$ 96, covering various boiling scenarios. The dataset consists of velocity_x and velocity_y as input channels (batch, 2, 288, 96), predicting the velocity field in the same shape. Since the original width (96) represents half the bubble, results are symmetrically expanded to 192 for full visualization.

Data Statistics



Data Visualization



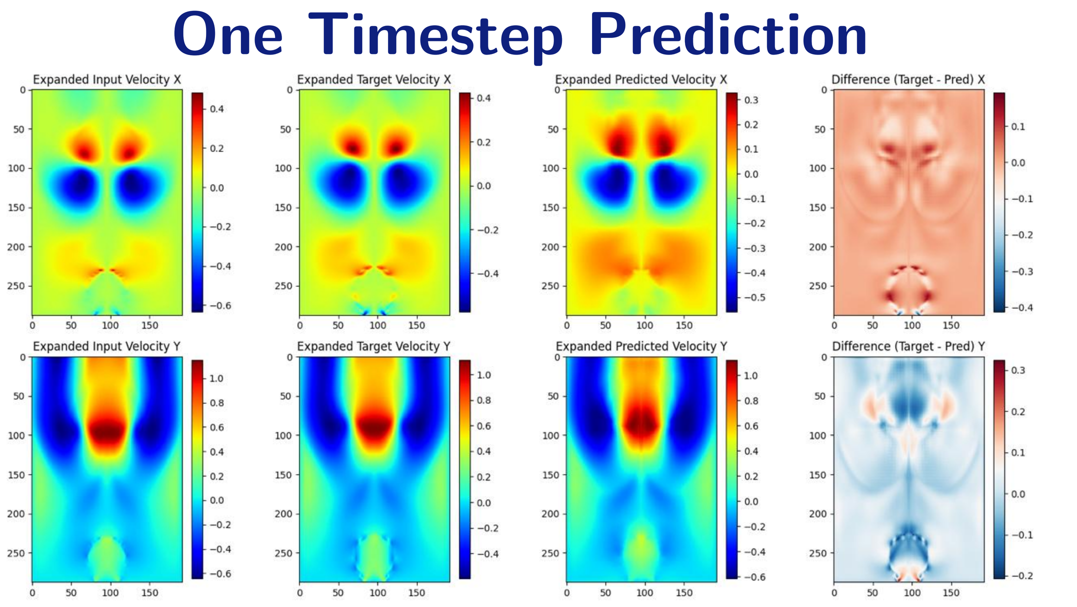
UNET MODEL

The UNet model is a fully convolutional network optimized for velocity field prediction. Its encoder-decoder structure efficiently captures spatial patterns in fluid dynamics.

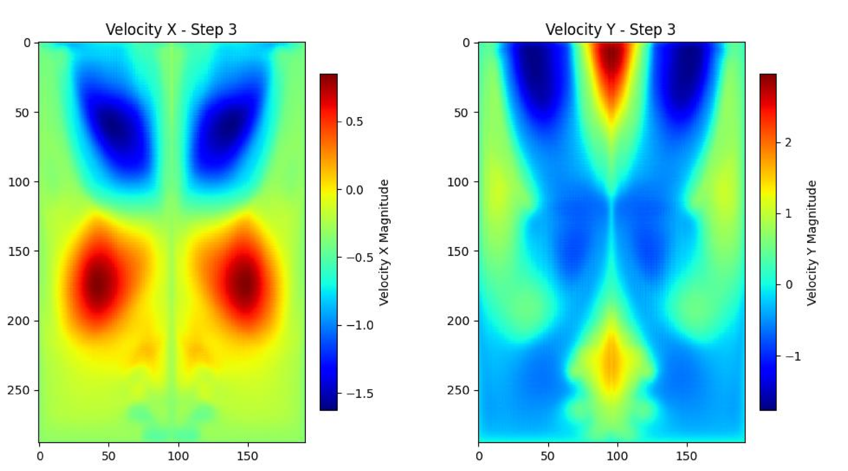
Architecture Overview:

- 3 Encoder layers (Downsampling with Conv2D + MaxPool2D)
- 1 Bottleneck layer (Deep feature extraction)
- 3 Decoder layers (Upsampling with ConvTranspose2D + concatenation)
- 1 Final convolution layer (Projection to velocity field)

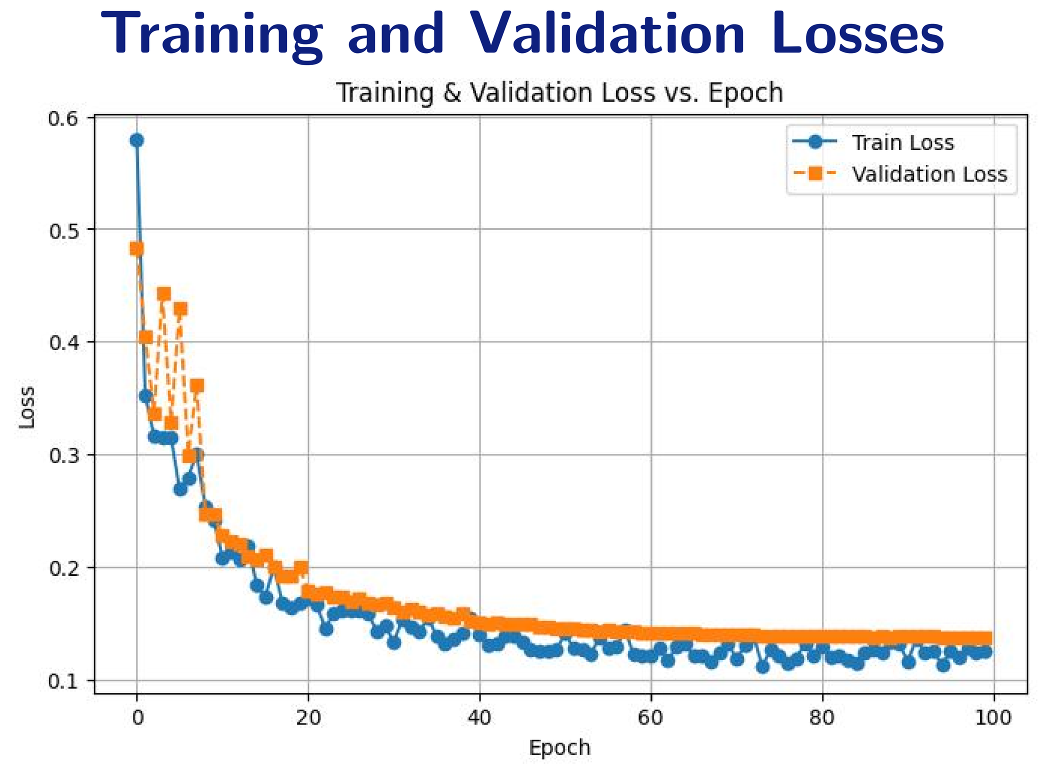
One Timestep Prediction



Multiple Timestep Prediction



Training and Validation Losses



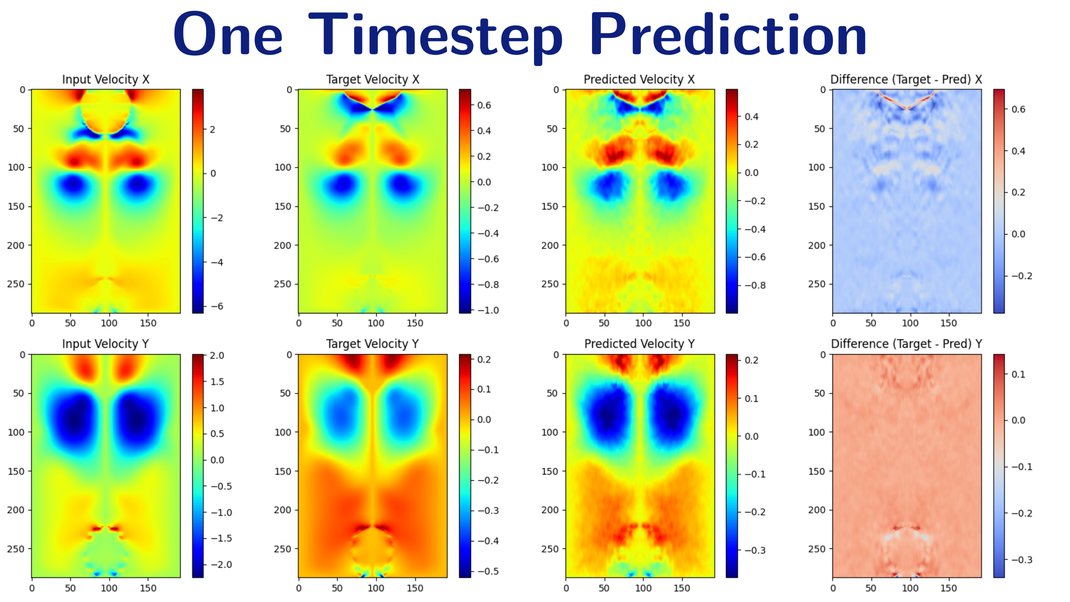
FNO MODEL

The Fourier Neural Operator (FNO3d) model is designed for learning spatiotemporal dependencies, particularly for predicting velocity fields.

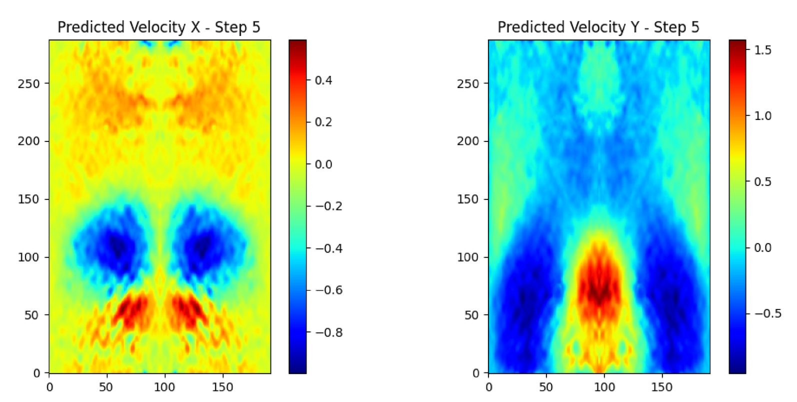
Architecture Overview:

- 1 Initial projection layer (fc0 - Linear transformation to feature space)
- 3 Spectral Convolution layers (SpectralConv3d - Fourier Transform + learned spectral filters)
- 3 Pointwise Convolution layers (Conv1d - Local feature processing)
- 2 Fully Connected layers (fc1, fc2 - Final velocity field prediction)

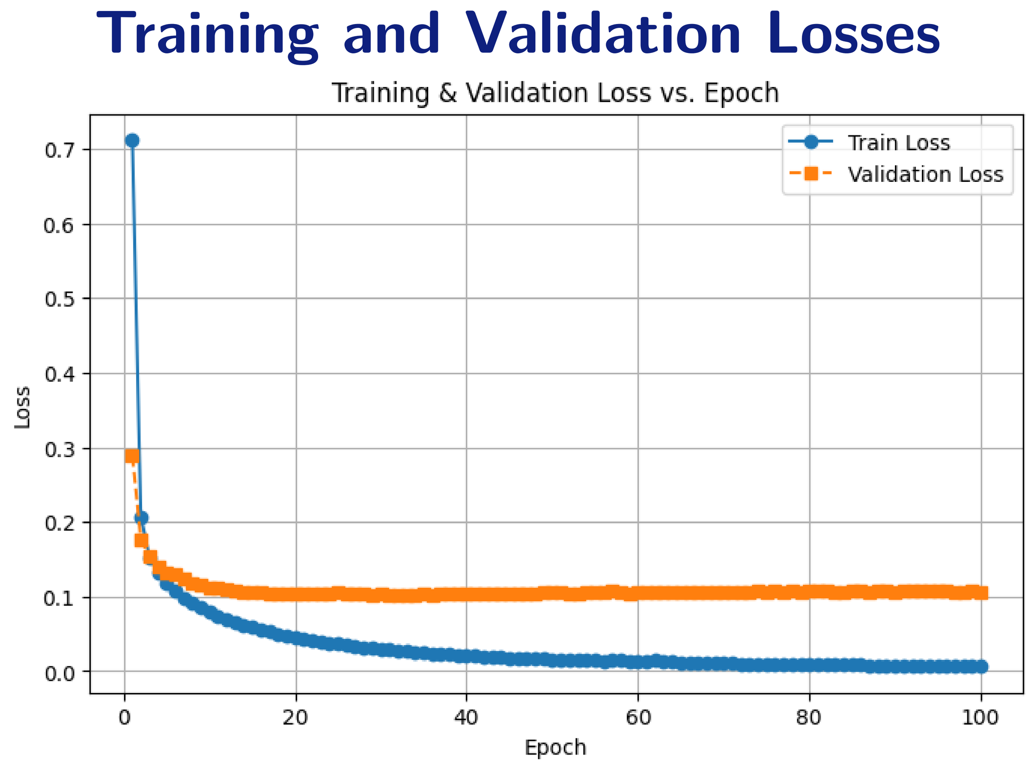
One Timestep Prediction



Multiple Timestep Prediction



Training and Validation Losses



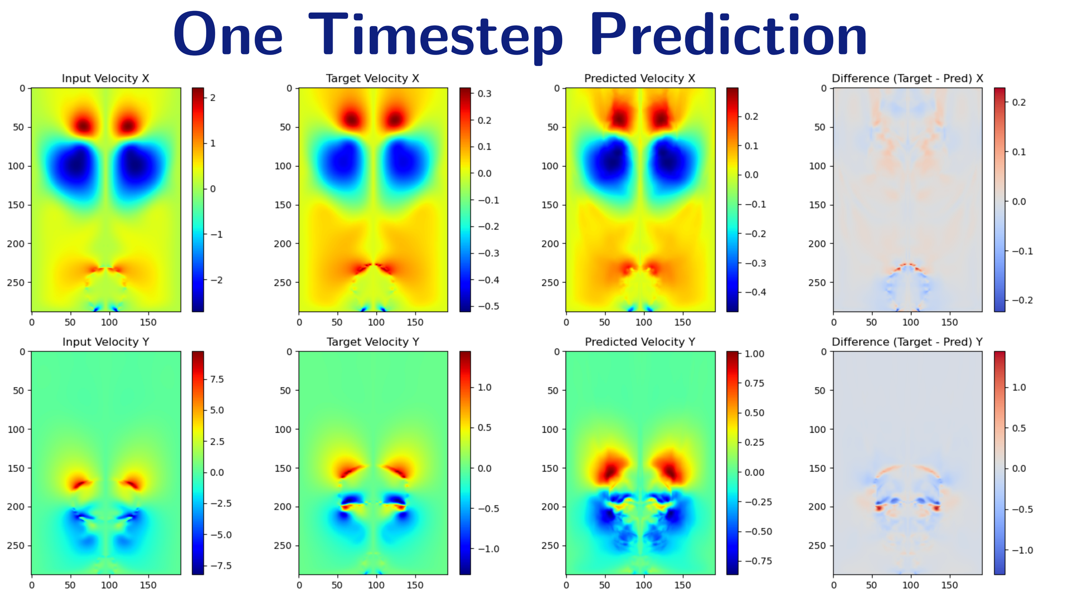
CONVLSTM MODEL

This ConvLSTM-based model is designed for spatiotemporal velocity field prediction, capturing both local spatial dependencies (CNN) and temporal dependencies (LSTM).

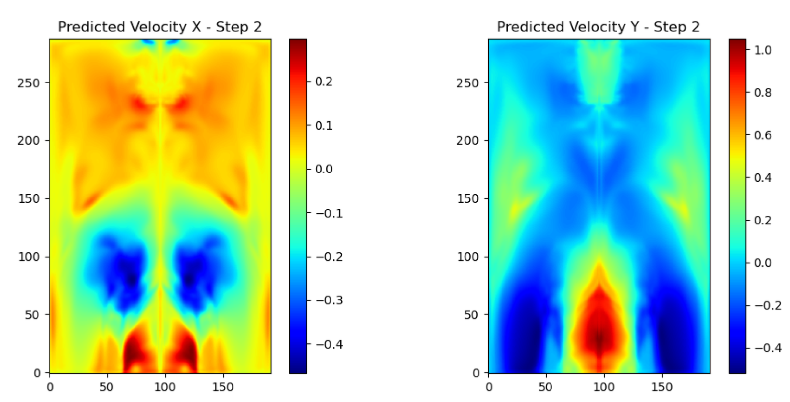
Architecture Overview:

- 3 ConvLSTM layers (Each layer consists of a Conv2D operation within the LSTM cell)
- 1 Bottleneck layer (Deep feature extraction over time)
- 1 Fully connected projection layer (fc1 - Maps hidden features to 128)
- 1 Final output layer (fc2 - Maps to 2 velocity components: velocity_x, velocity_y)

One Timestep Prediction



Multiple Timestep Prediction



Training and Validation Losses