
PPT Title:

Hybrid Deep Learning and Physics-Based Modeling for Efficient Fluid Flow Prediction

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Slide 1: Title Slide

- **Title**: Hybrid Deep Learning for Fluid Dynamics
- **Subtitle**: Combining Data-Driven and Physics-Based Models
- **Presented by**: [Your Name], [Affiliation]
- **Date**

Slide 2: Motivation

- Traditional CFD is accurate but slow.
- Complex geometries and turbulent flows take excessive time to simulate.
- Real-time or large-scale applications are limited by computational cost.
- **Need**: Faster yet reliable prediction methods.

Slide 3: Problem Statement

> "Traditional Computational Fluid Dynamics (CFD) methods are highly accurate but computationally expensive, especially for complex geometries and turbulent flows. This project aims to develop a deep learning-based hybrid model that combines data-driven methods and physics-informed modeling to predict fluid flow behavior more efficiently and accurately."

- Breakdown:
  - CFD → Accurate but slow
  - DL → Fast but may ignore physics
  - Goal: Combine both for speed + accuracy

Slide 4: Project Objective

- Develop a hybrid deep learning model to predict fluid behavior.
- Train on both CFD simulation data and real-world measurements.
- Ensure predictions follow physical laws (e.g., Navier-Stokes).
- Enable real-time, physically-consistent predictions.

Slide 5: Key Features

- 🔍 **Data-Driven Predictions** – Learn from CFD + experimental data
- 🔄 **Hybrid Modeling** – Combine physics and ML
- 🌪️ **Handles Complexity** – Turbulent flows, boundary conditions
- ⚡ **Efficiency** – Much faster than traditional solvers

Slide 6: Workflow Overview (Flowchart)

Include a visual showing the pipeline:

1. Data Collection (CFD + real-world)
2. Preprocessing & EDA

3. Model Training (CNN + PINNs)
4. Evaluation (error metrics + physical checks)
5. Deployment

Slide 7: Data Collection

- **CFD Data**:
    - Simulate laminar, turbulent, and complex geometries using OpenFOAM/ANSYS
- **Experimental Data**:
    - Wind tunnels, sensors, lab flow tests
- Parameters: Pressure, velocity, temperature, geometry

Slide 8: Model Design

- **CNN** for spatial data (e.g., flow fields)
- **ANN** for scalar predictions (e.g., avg. turbulence)
- **PINNs** for embedding physics (Navier-Stokes)
- **Loss Function** includes data loss + PDE residuals

Slide 9: Evaluation Strategy

- **Metrics**:
    - Mean Absolute Error (MAE)
    - Root Mean Squared Error (RMSE)

    - Physics consistency checks
- **Validation**:
    - Use unseen CFD and experimental data
    - Cross-validate with multiple scenarios

Slide 10: Benefits

- 🕒 Real-time predictions
- 📉 Reduced simulation cost
- 📈 Scalable to complex systems
- 🔁 Physically accurate results

Slide 11: Applications

- Aerospace (airfoil design)
- Meteorology (weather prediction)
- Automotive (aerodynamic modeling)
- Biomedical (blood flow in arteries)

Slide 12: Future Scope

- Extend to 3D flows and multi-phase systems
- Deploy on cloud for large-scale real-time use
- Integrate with digital twins in engineering systems

Slide 13: Conclusion

- Hybrid deep learning + physics = efficient, accurate, and scalable fluid simulation
- This approach bridges the gap between data science and physics in engineering

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Slide 14: Q&A

- “Questions & Discussions”
