

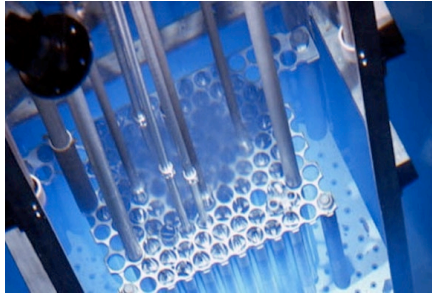


High-Frequency Sequence Regression and Multimodal Fusion for Nonintrusive Thermal Monitoring

Christy Dunlap, Hari Pandey, Jackson Marsh, Ethan Weems, Han Hu
Department of Mechanical Engineering
University of Arkansas, Fayetteville, AR 72701

Background: Challenges of Thermal Management

Nuclear Reactor



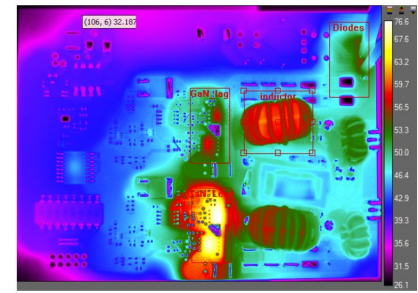
Concentrated Solar Power and PV



Computer Chips and Data Centers



Wide bandgap Power Electronics

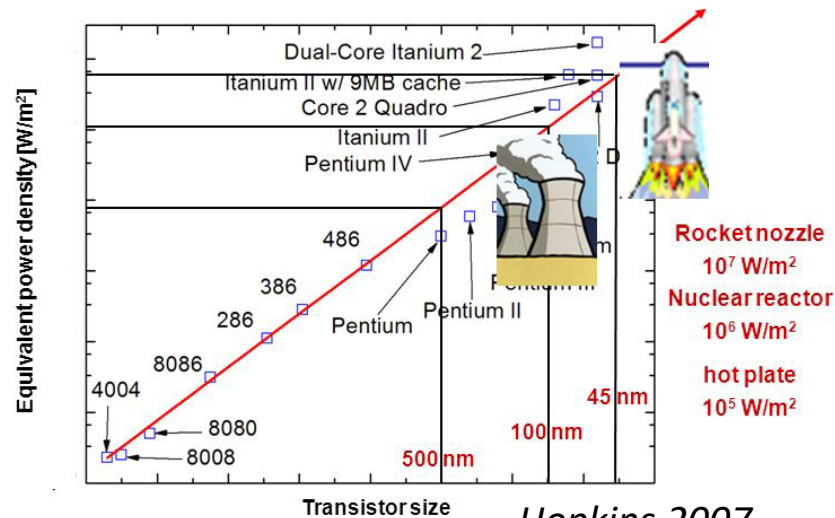


Penn State Breazeale Plant

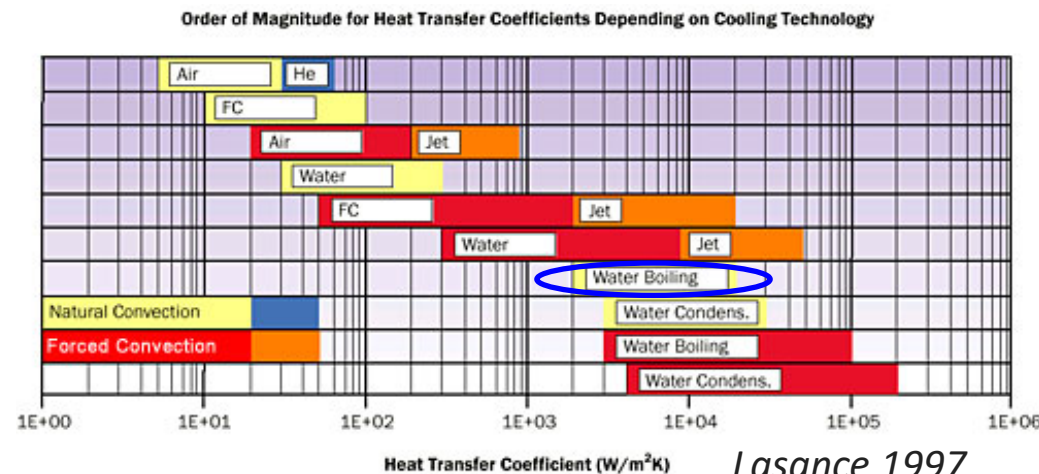
Solana Generating Station

3M (using Intel Chips)

Navitas Power Amplifier



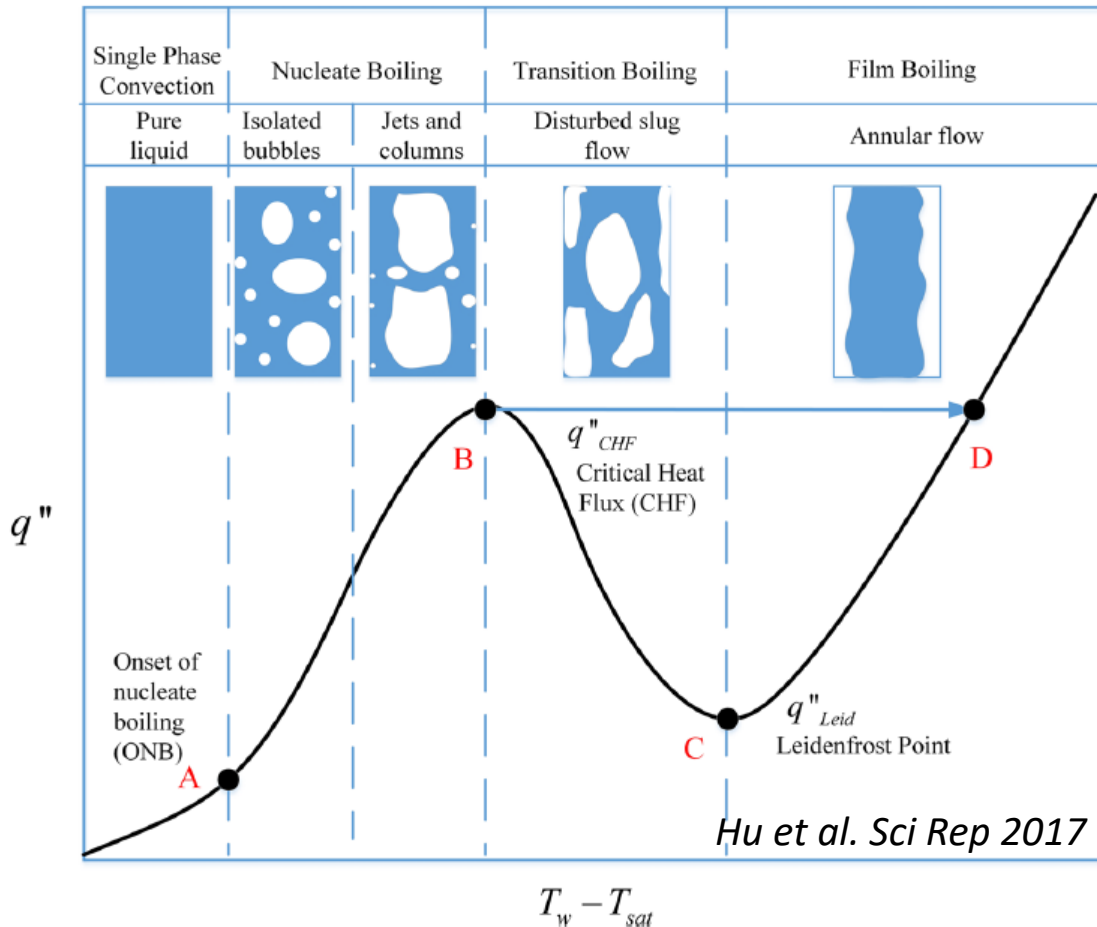
Hopkins 2007



Lasance 1997

Practical Limit of Boiling Heat Transfer

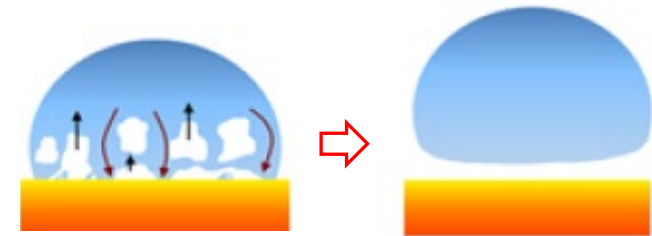
Boiling Regimes in a Representative Boiling Curve



Heat transfer coefficient (HTC): $HTC = q'' / (T_w - T_{sat})$

Critical Heat Flux (CHF): A catastrophic point of failure

Point B: CHF



Nucleate boiling
(pre-CHF)

Film boiling
(post-CHF)

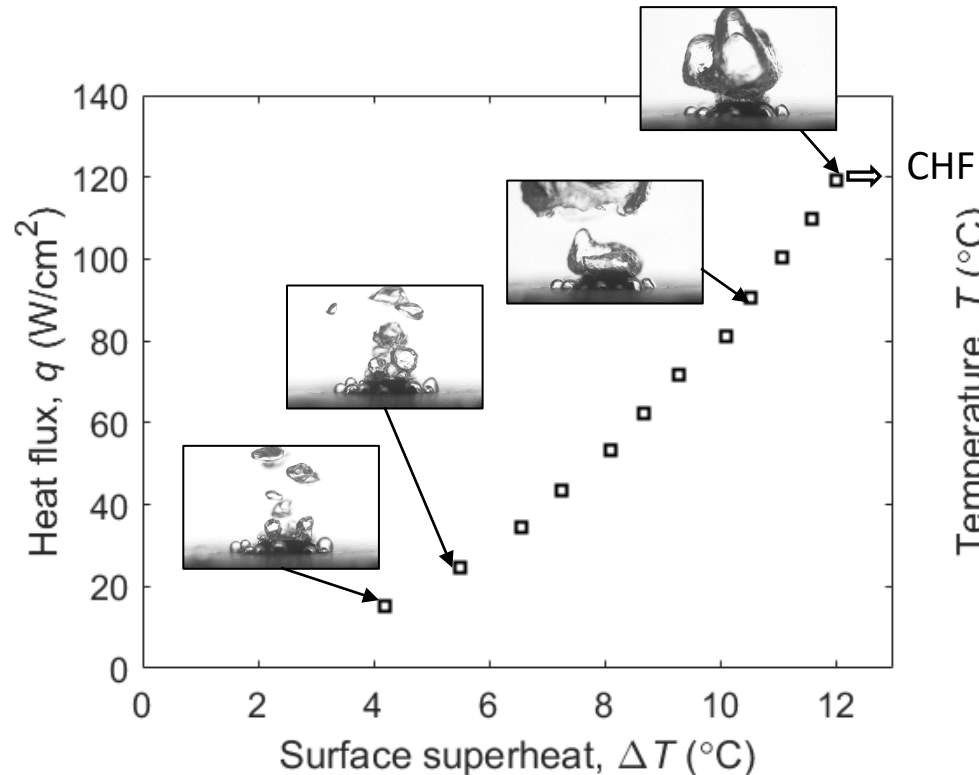
Sheehan et al. UNL

Immediately after CHF is triggered:

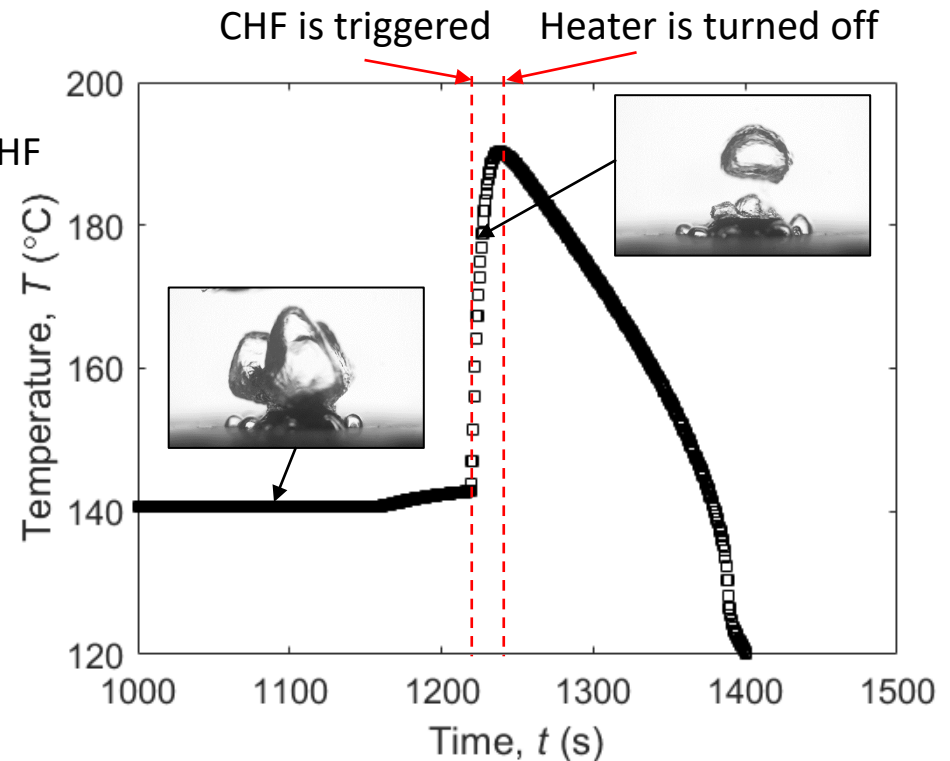
- HTC drops by orders of magnitude;
- Surface temperature increases by hundreds of degrees.

Steady-State Boiling Curve and CHF Condition

Steady-State Boiling Curve on Polished Copper Surface



CHF Condition Observed During Pool Boiling on Polished Copper Surface



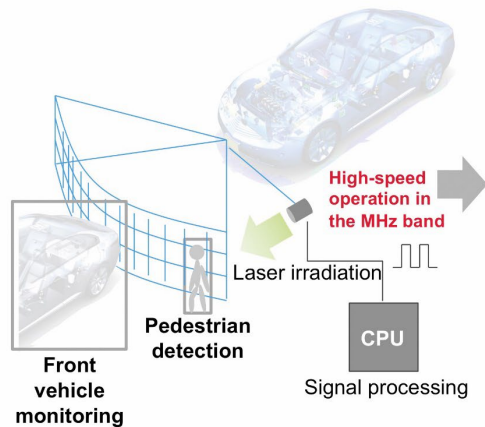
When CHF is triggered, heater temperature increases rapidly ($\sim 150^{\circ}\text{C}/\text{min}$).

Thermal Management Challenges Due to Dynamic Loads

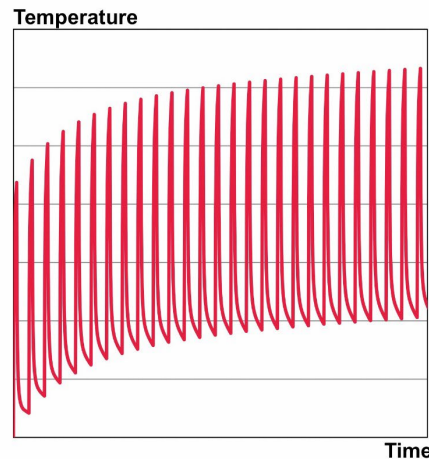
Transient heating conditions are very common in microelectronics, radio-frequency power amplifiers, vehicles and airliners.

Transient heating in the advanced driver-assistance systems

Pedestrian detection by laser radar

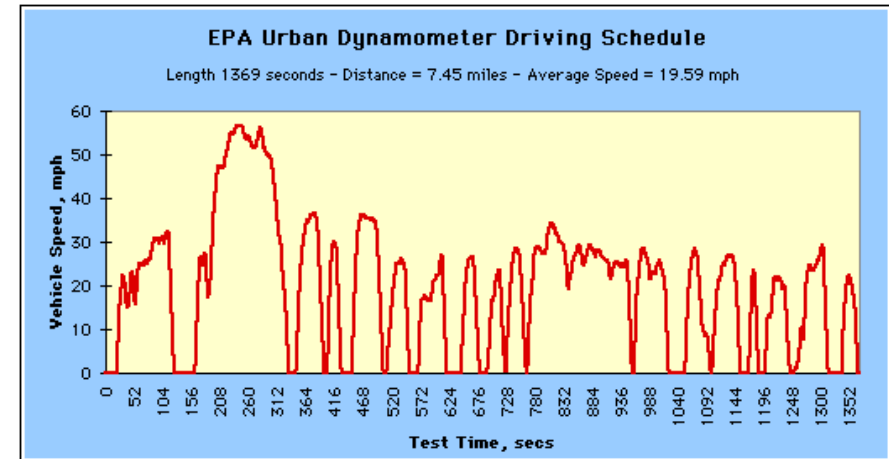


Transient heat analysis results



Shinoda, Electronics Cooling 2019

EPA Urban Dynamometer Driving Schedule

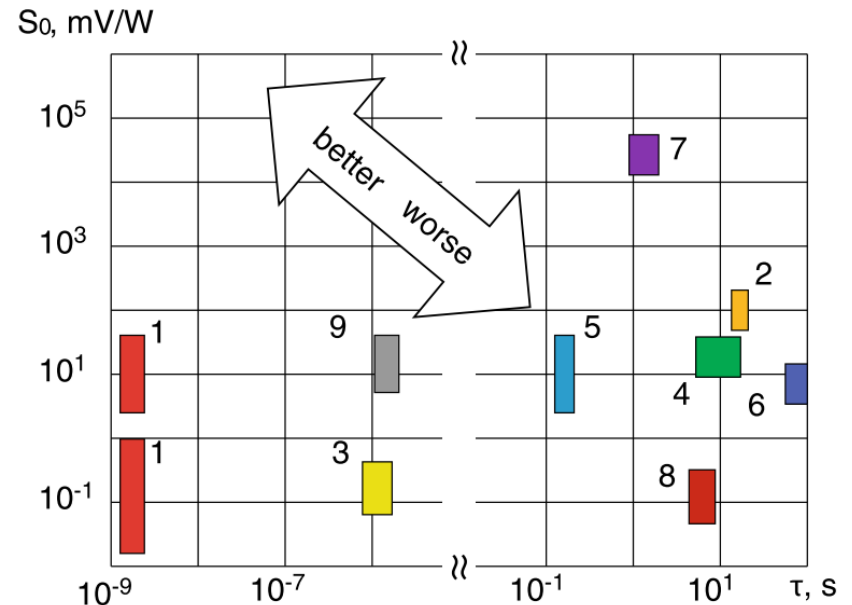
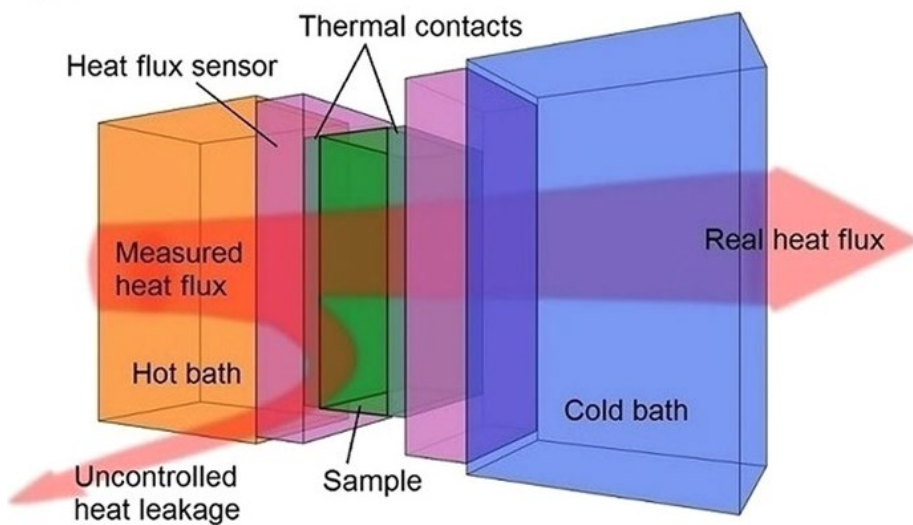


EPA

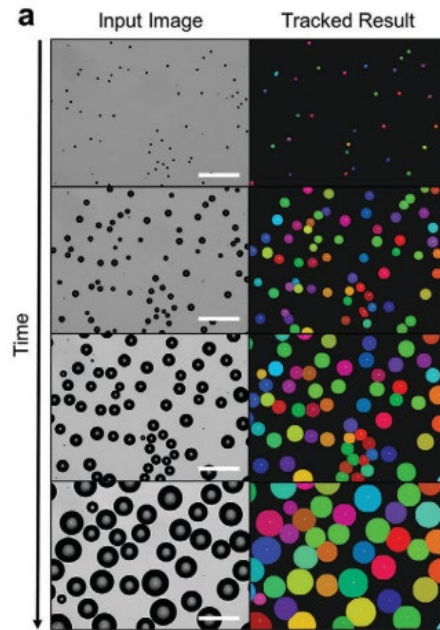
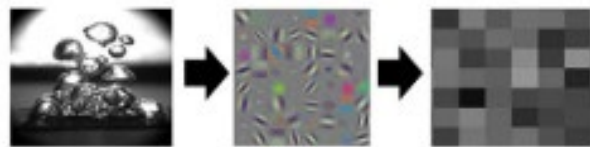
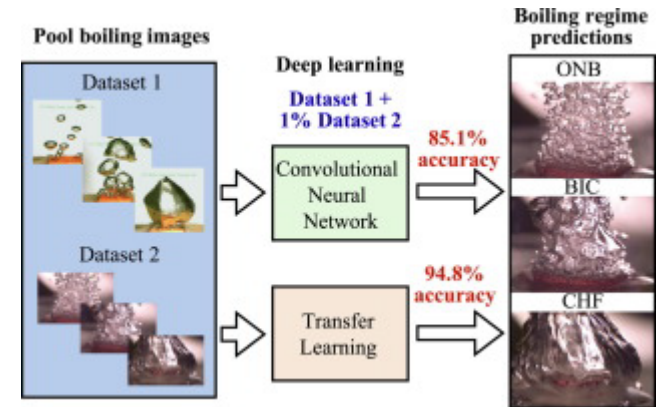
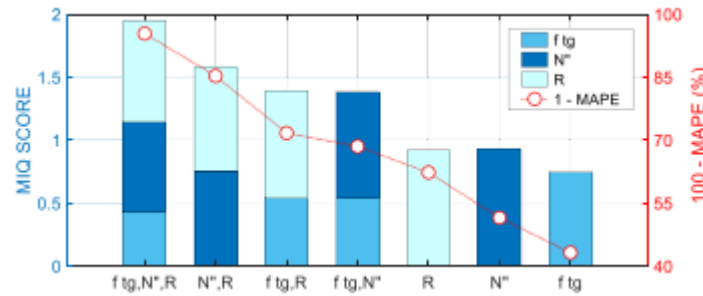
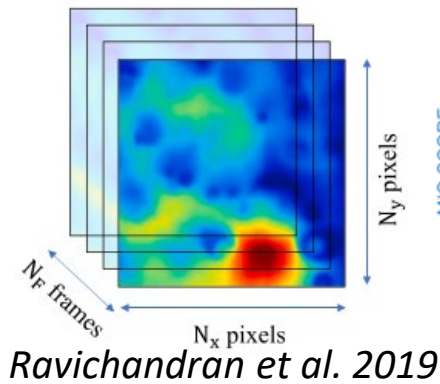
Heat Flux Measurements in Power Systems

Surface-mounted sensors

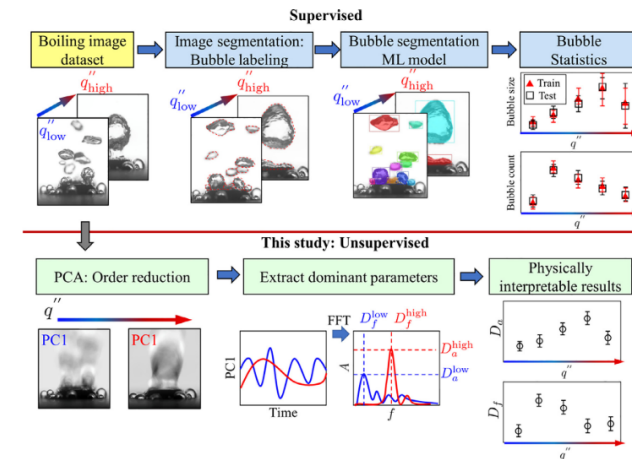
- Transverse thermoelectric effect method
- Temperature gradient method
- Joule heating effect method



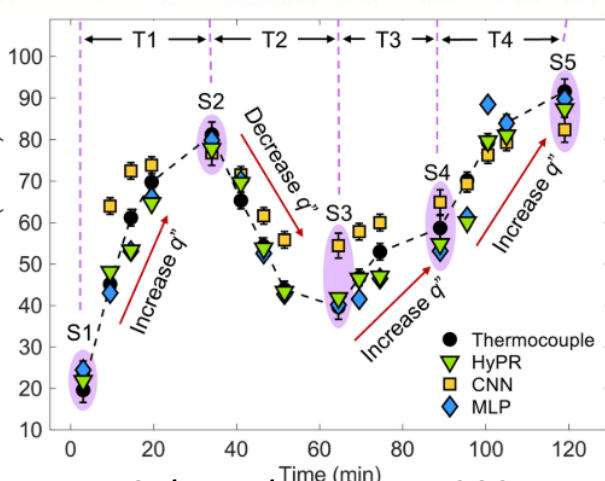
Deep Learning Strategies for Visualization-Based Analysis of Two-Phase Heat Transfer



Rassoulinejad-Mousavi et al., ATE, 2021



Rokoni et al., IJHMT, 2022

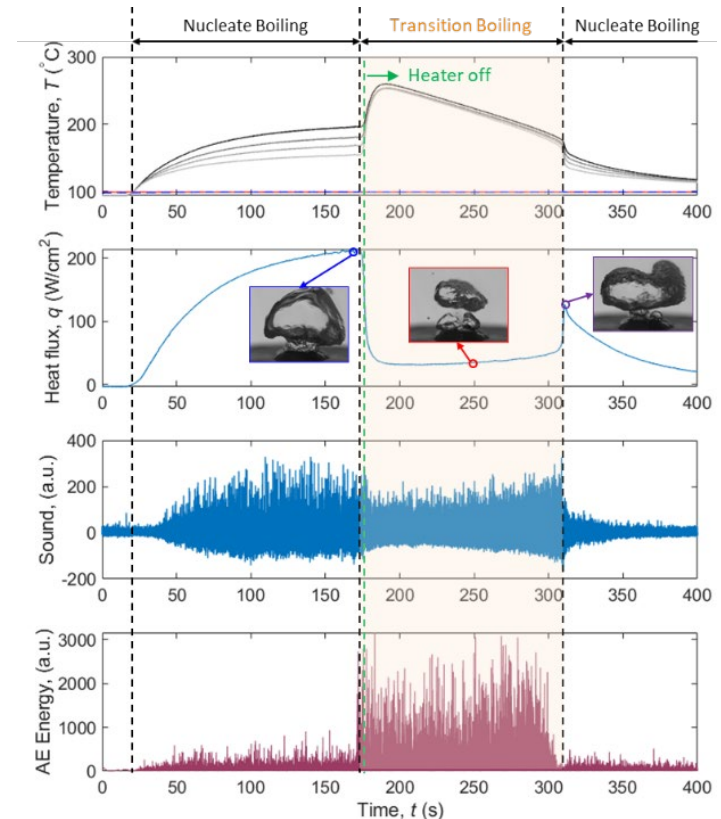
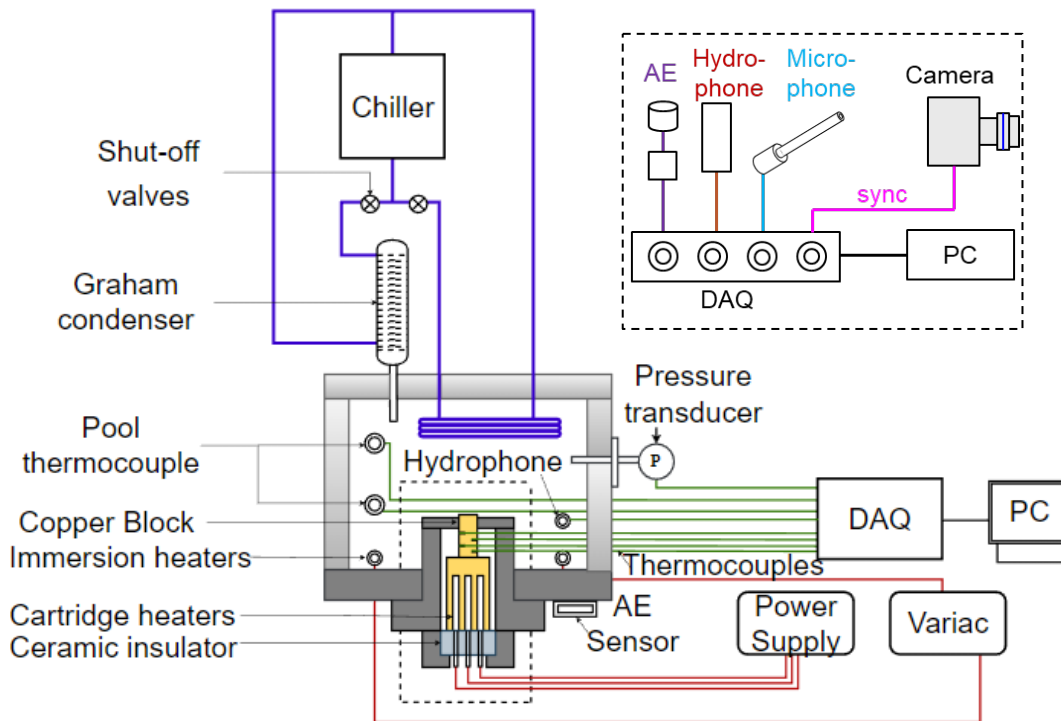


Suh et al., Sci Rep, 2021

Suh et al., Adv Sci, 2021

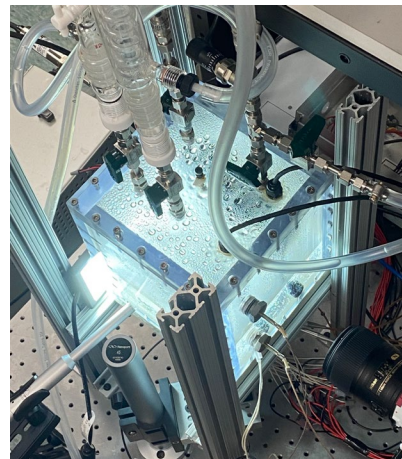
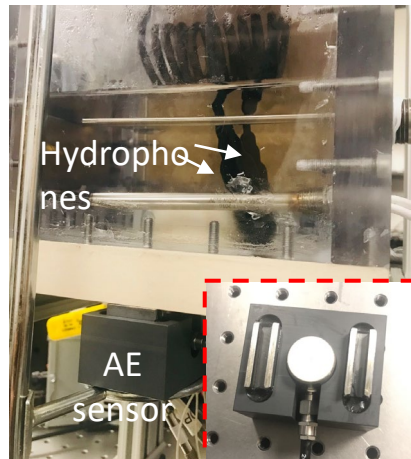
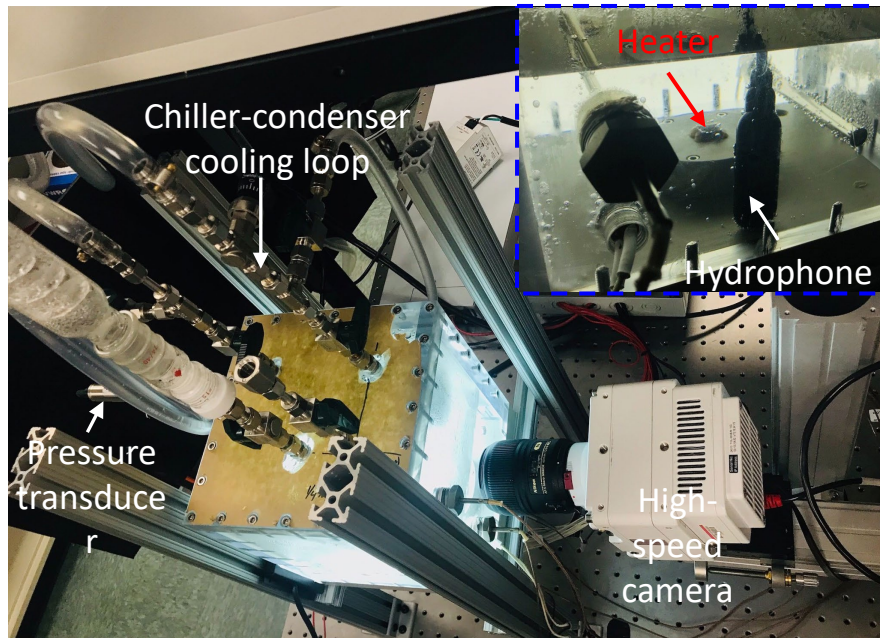
Pool Boiling Facility with Multimodal Sensing

Synchronized multimodal Sensing: i) High-speed imaging, ii) acoustic – hydrophone, iii) acoustic – microphone, iv) acoustic – AE sensor, v) temperature profiles, vi) pressure.

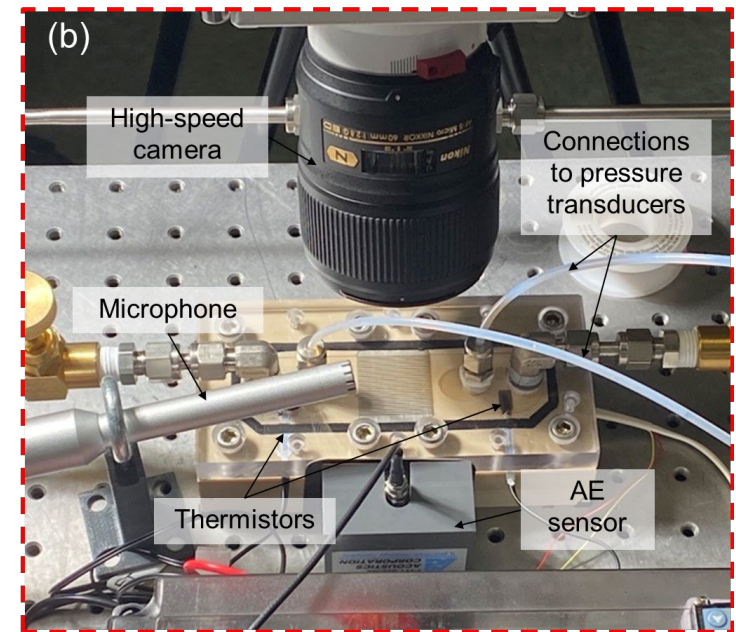
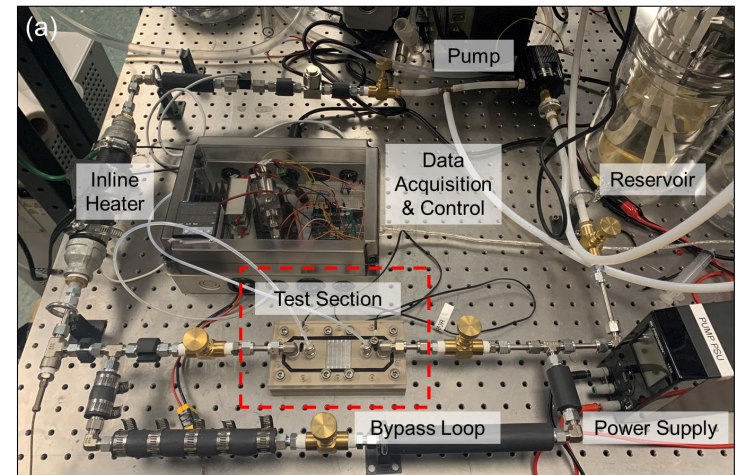


Multimodal Sensing in Boiling Systems

Pool Boiling

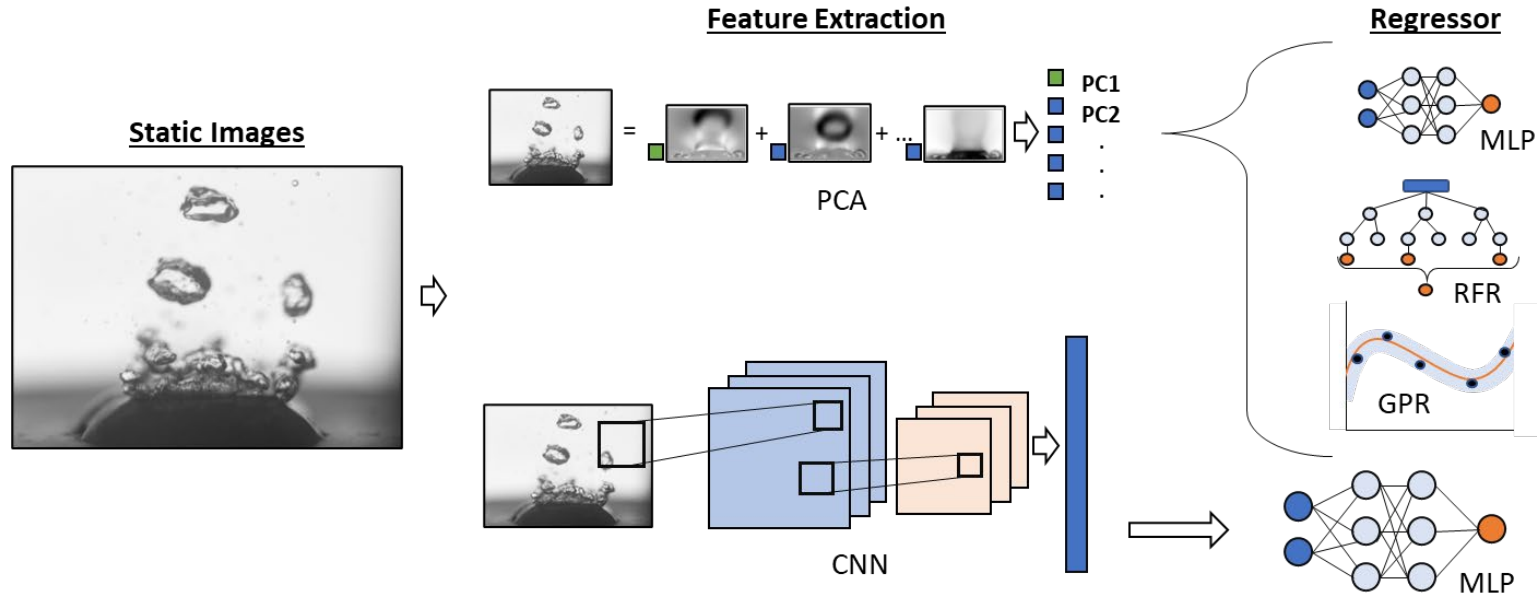


Flow Boiling

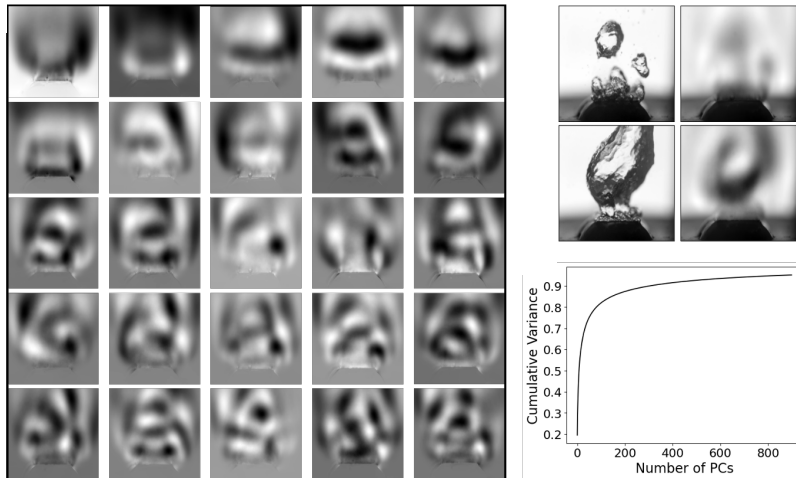


1. Visualization-Based Heat Flux Measurement

Existing Methods: Static Image-Based Heat Flux Prediction



Principal Component Analysis (PCA)



K-means Clustering

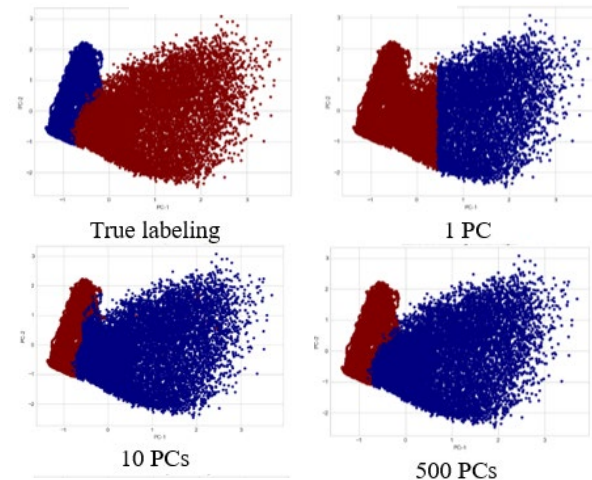
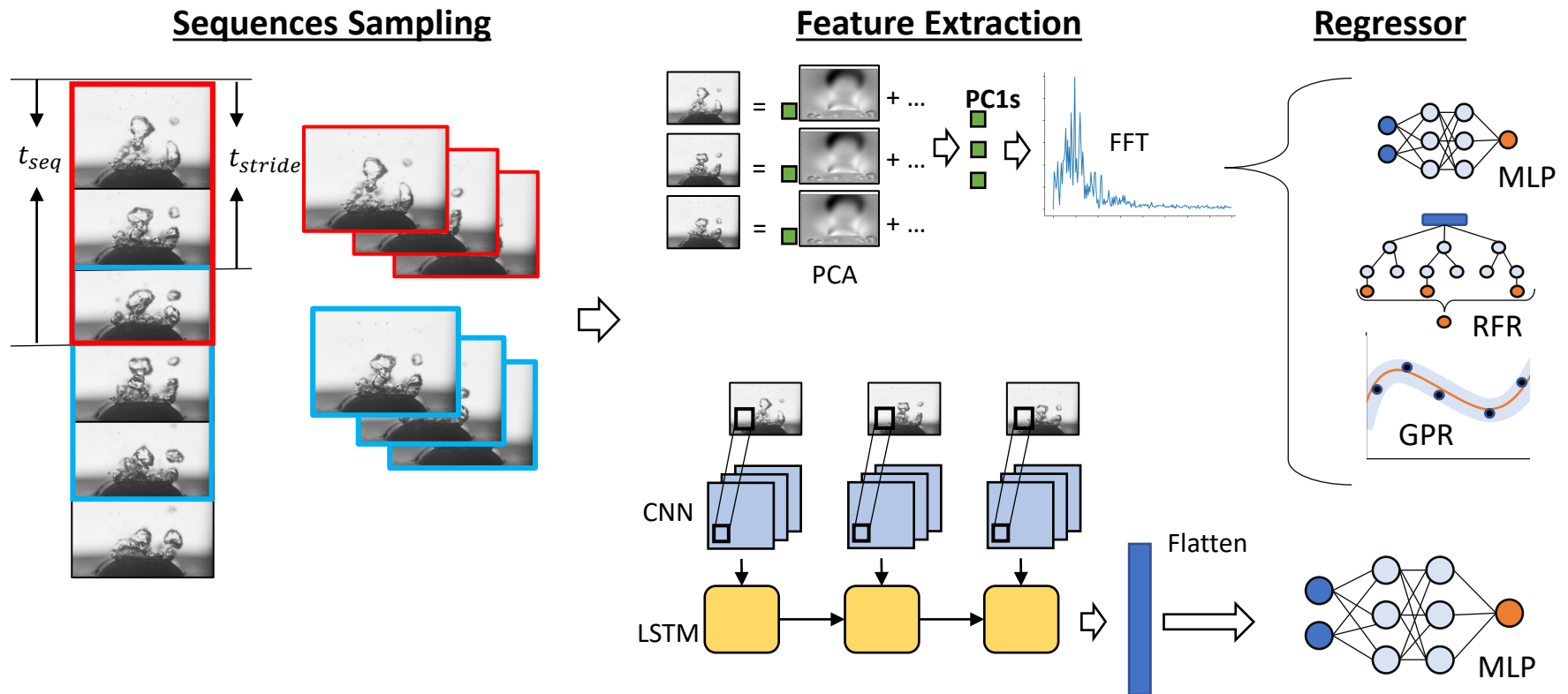


Image Sequence-Based Heat Flux Prediction



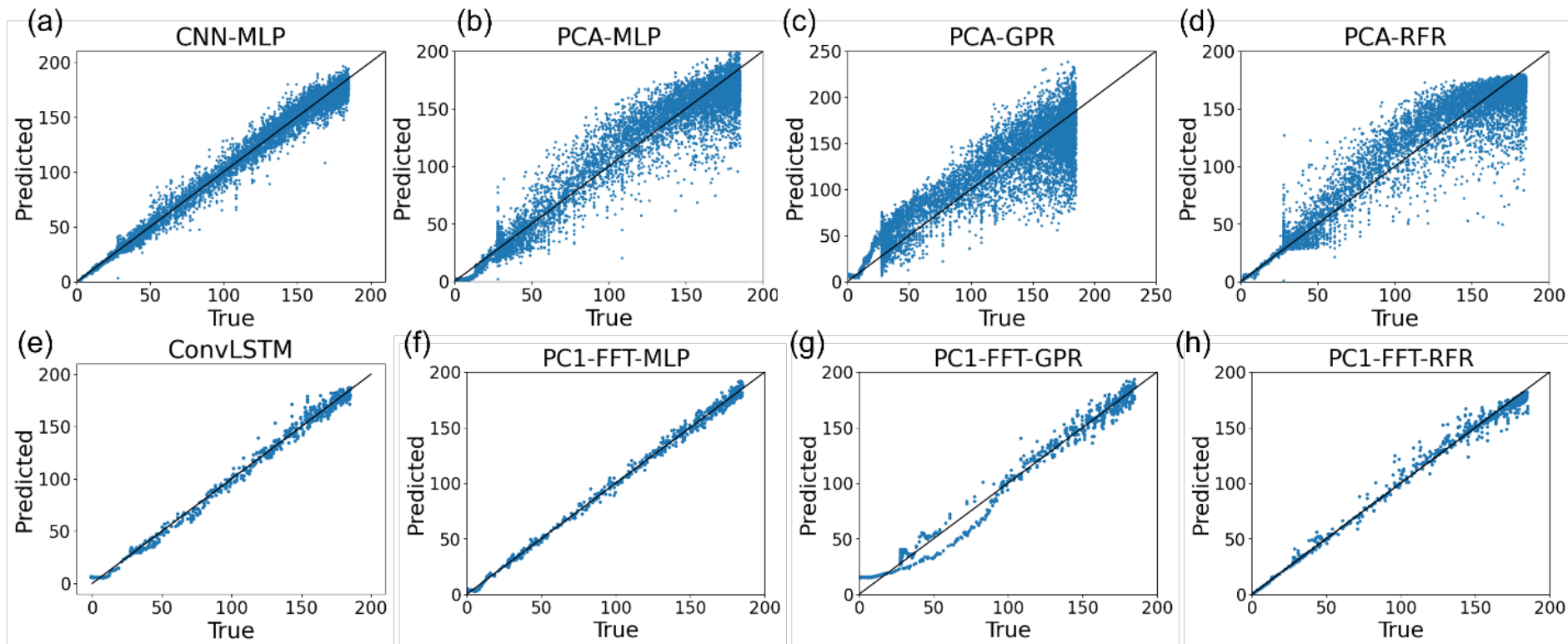
Spatiotemporal Feature Extraction:

- PCA and Fast Fourier Transform (FFT)
- Convolutional Long Short-Term Memory (ConvLSTM)

Heat Flux Prediction Performance: Static vs. Sequential

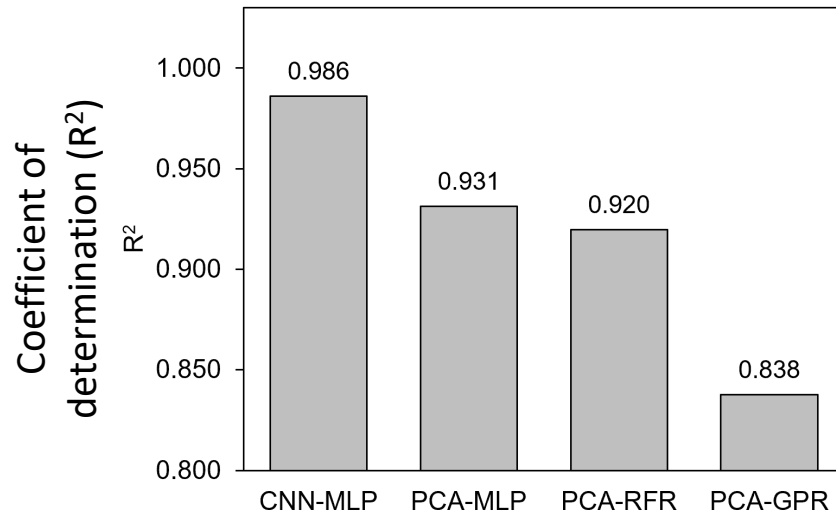
Model-predicted heat flux vs. true (experimental) heat flux for

- static image models: CNN-MLP, PCA-MLP, PCA-GPR, PCA-RFR, and
- Image sequence models: ConvLSTM, PC1-FFT-MLP, PC1-FFT-GPR, PC1-FFT-RFR

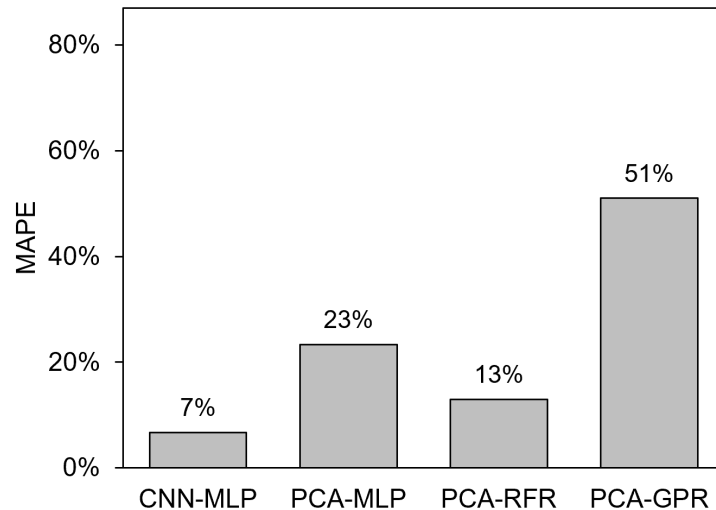


Heat Flux Prediction Performance: Static vs. Sequential

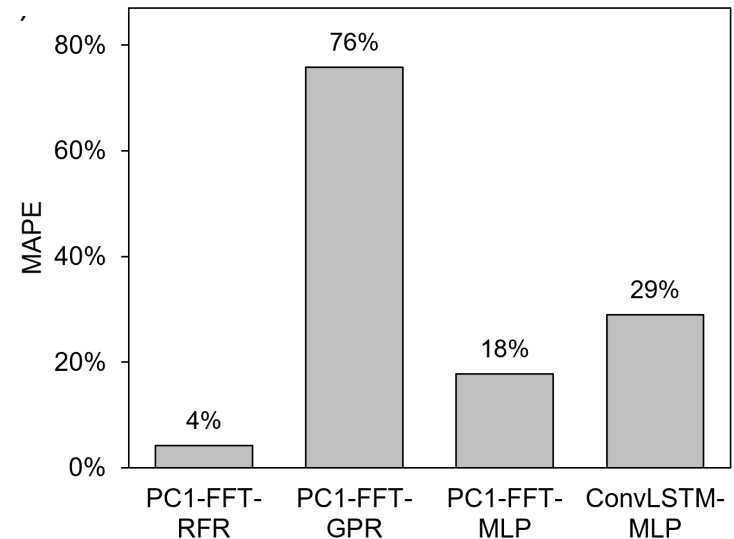
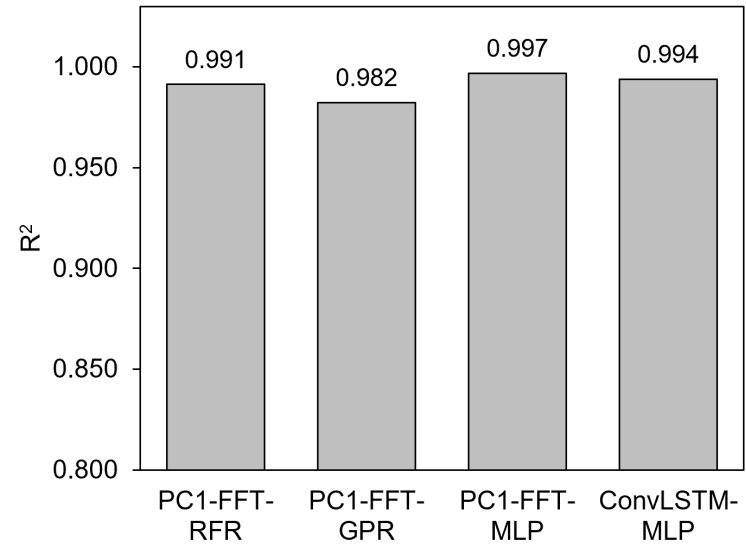
Static



Mean absolute percentage error (MAPE)

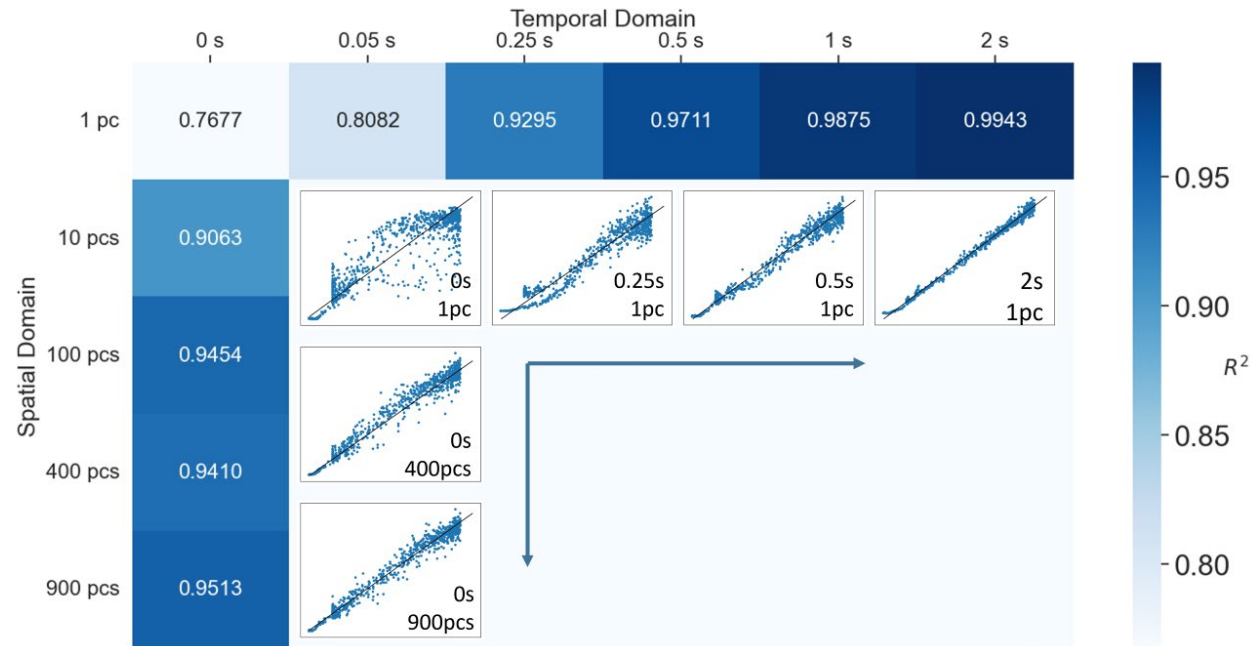
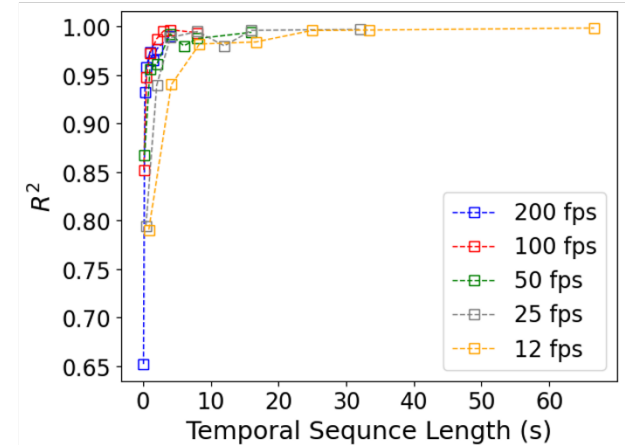
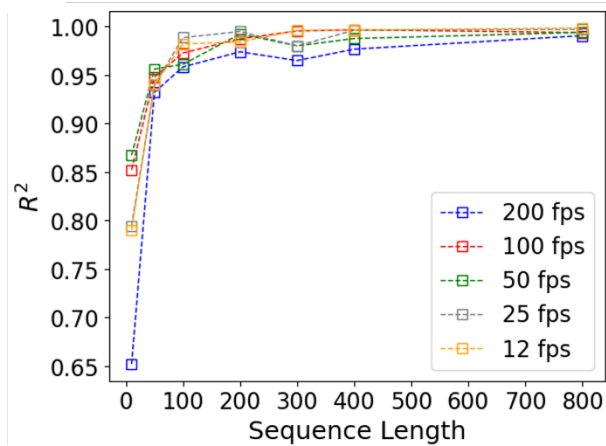


Sequential



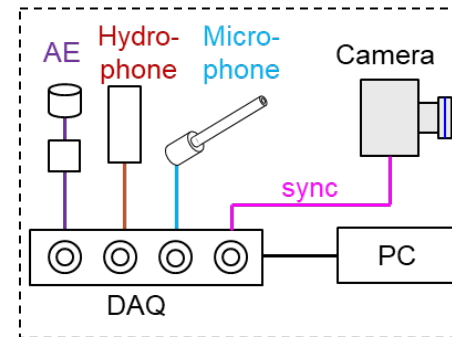
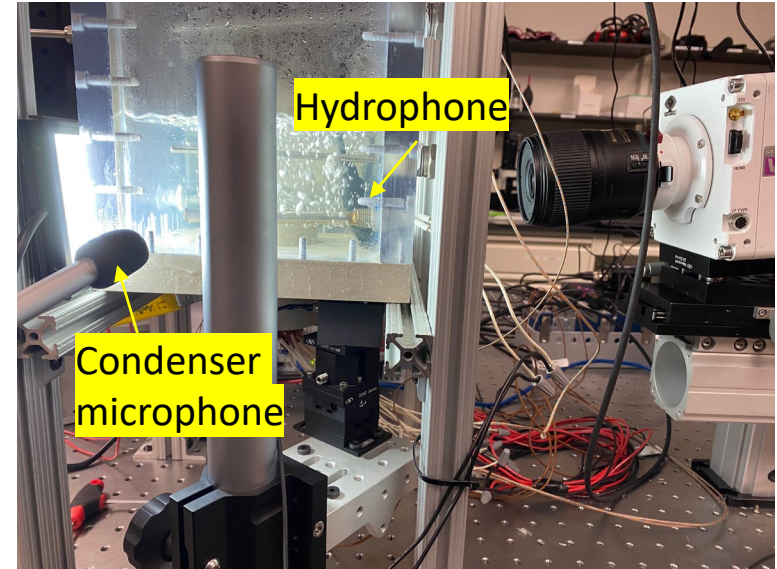
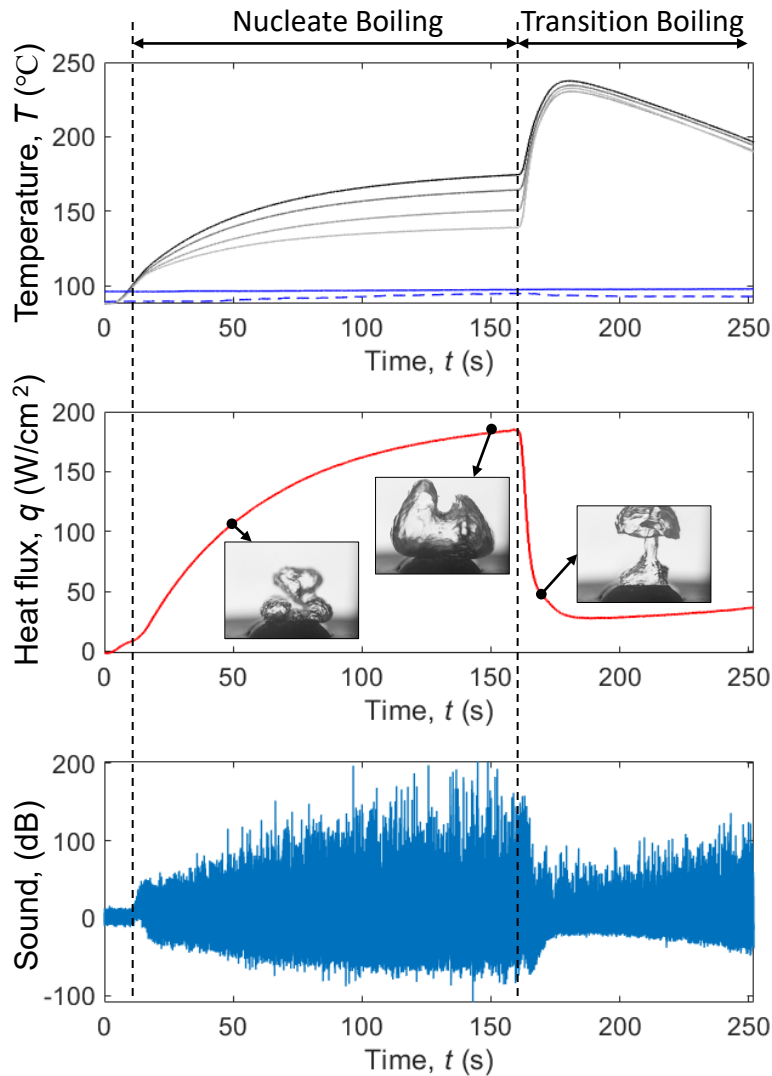
Role of Temporal Features of Bubble Dynamics on Heat Flux Predictions

- Temporal features play a critical role in heat flux predictions.
- Larger temporal length leads to better prediction performance.
- The frame rate doesn't play a critical role when it's beyond 25 fps.



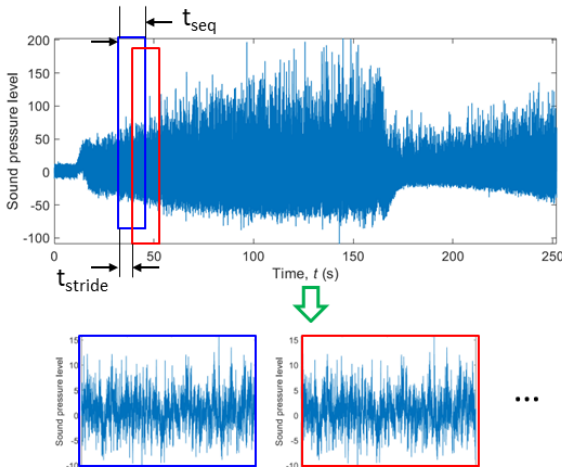
2. Acoustic-Based Heat Flux Measurement

Acoustic Sensing in Pool Boiling Experiments

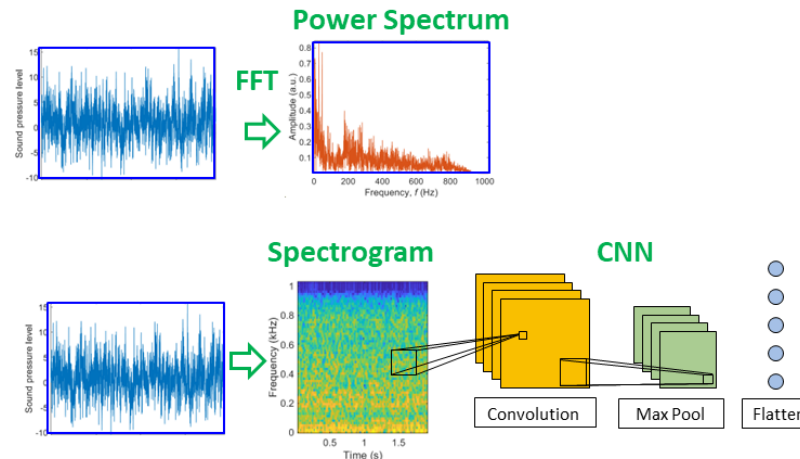


Machine Learning Algorithm for Heat Flux Prediction

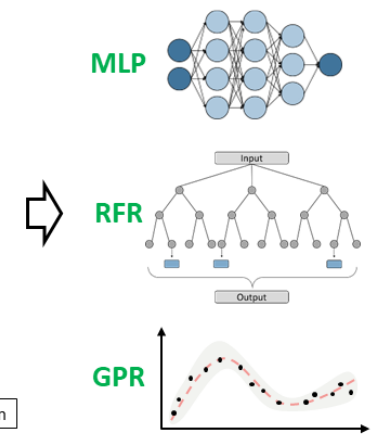
Step 1: Sequence Sampling



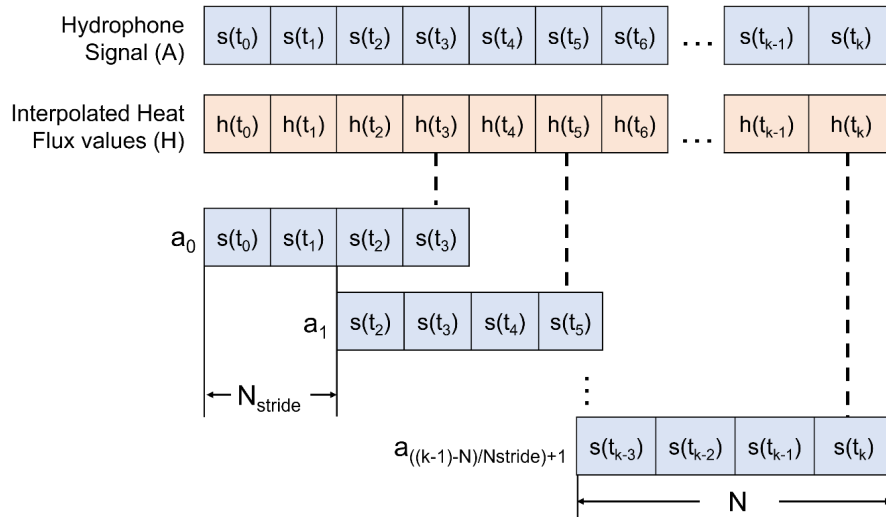
Step 2: Feature Extraction (2 options)



Step 3: Regression (3 options)



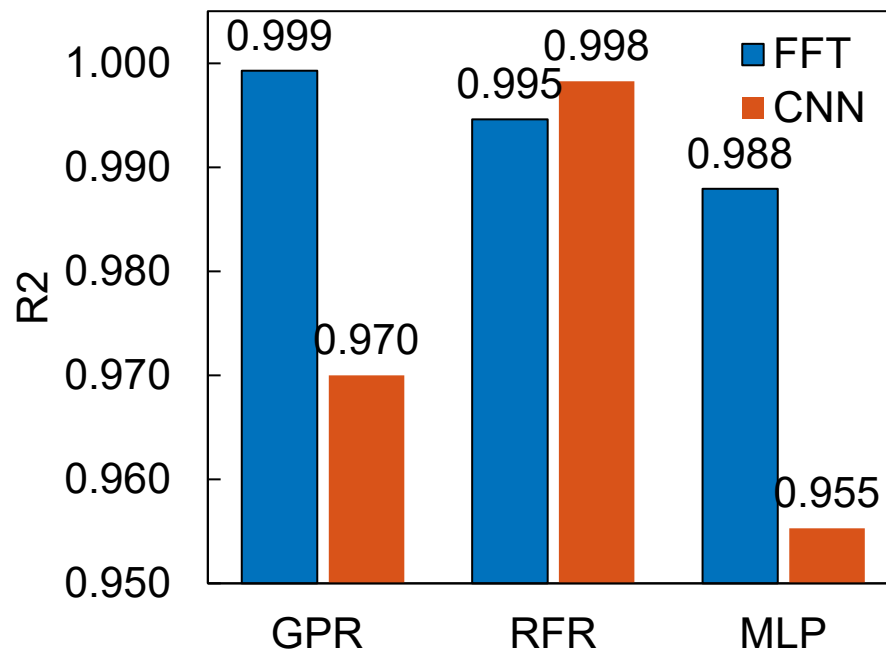
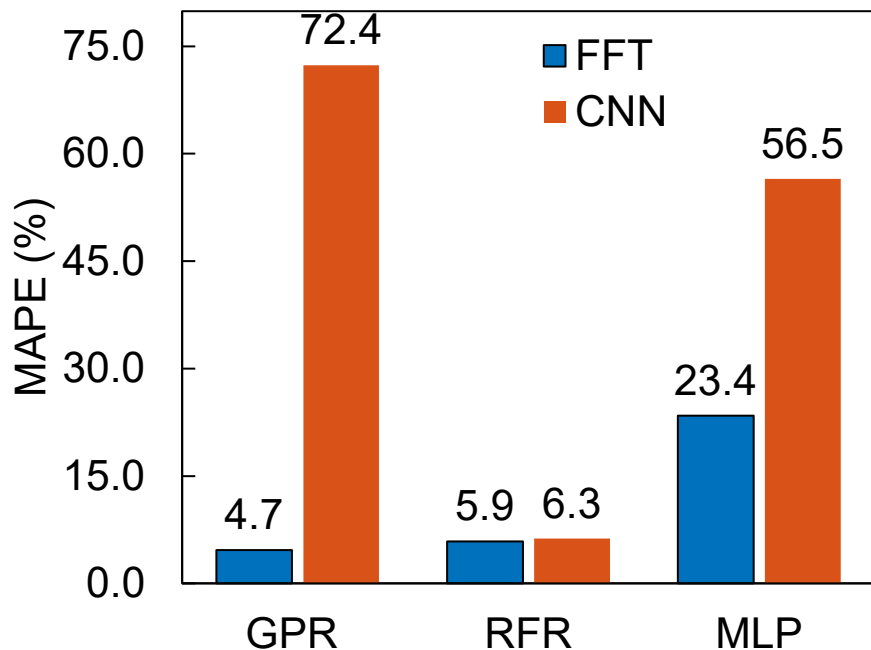
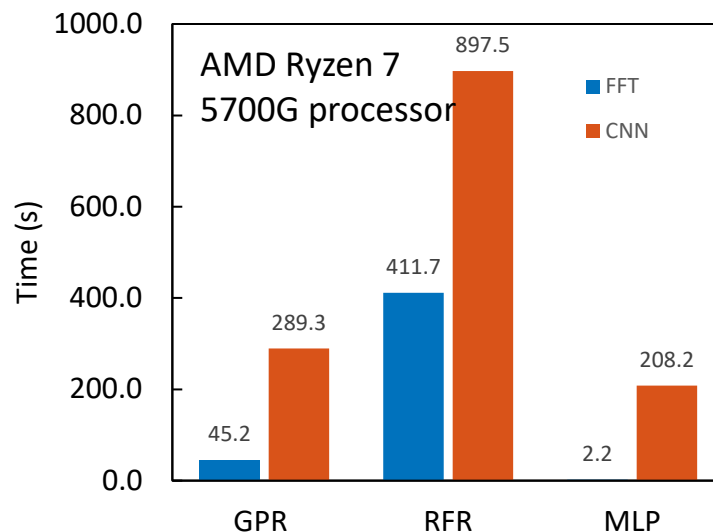
Sequence Sampling



- Sequence length: number of frames
- Stride: frames to skip
- Frame rate: sampling rate
- Temporal sequence length: sequence length / frame rate

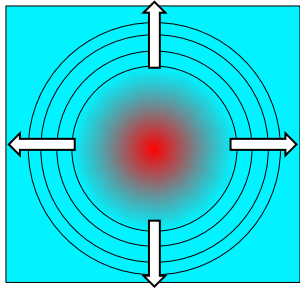
Model Performance and Computational Time for Training

FFT-GPR model leads to high performance and low computational time.

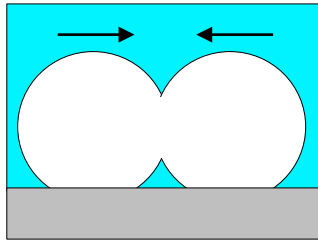


Physical Mechanisms of Acoustic Signals

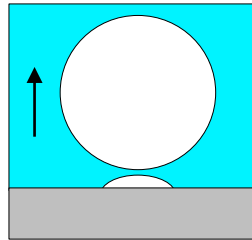
Thermal Expansion



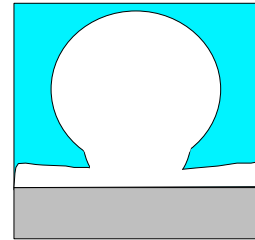
Bubble Ebullition



Bubble
Coalescence

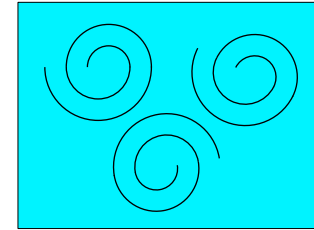


Bubble
departure

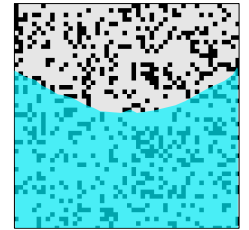


Critical Heat
Flux

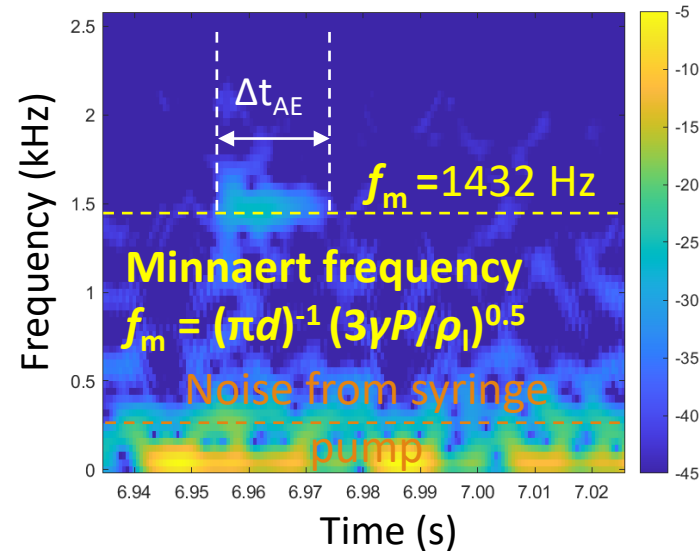
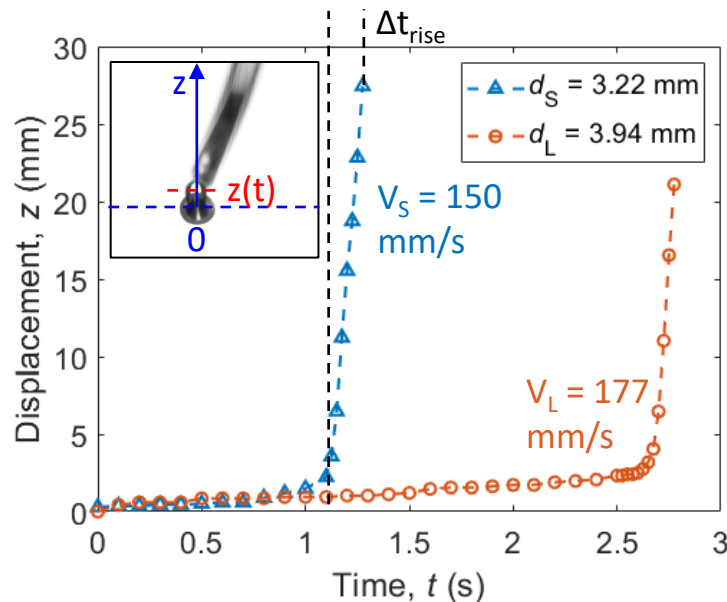
Flow-Structure Interaction



Convection

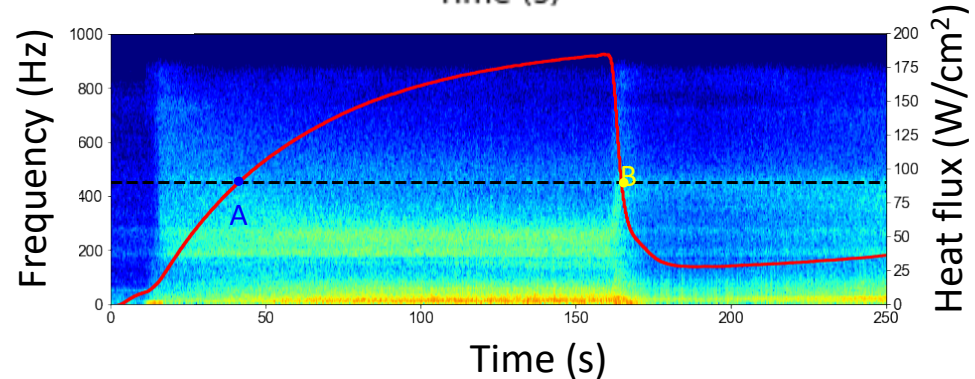
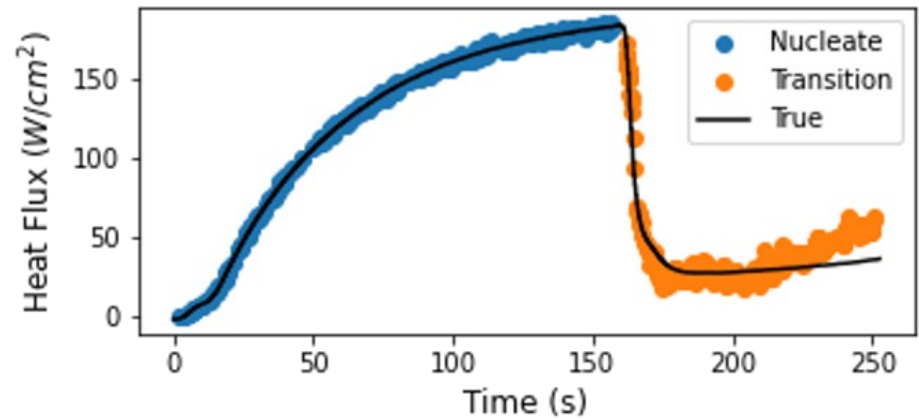
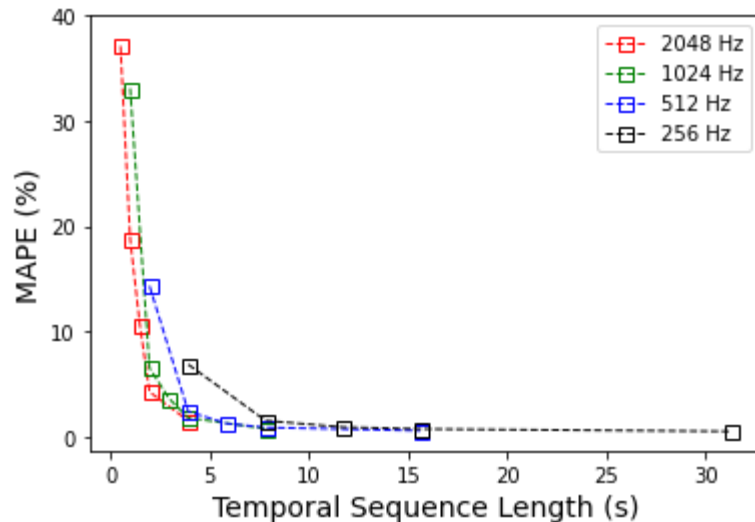
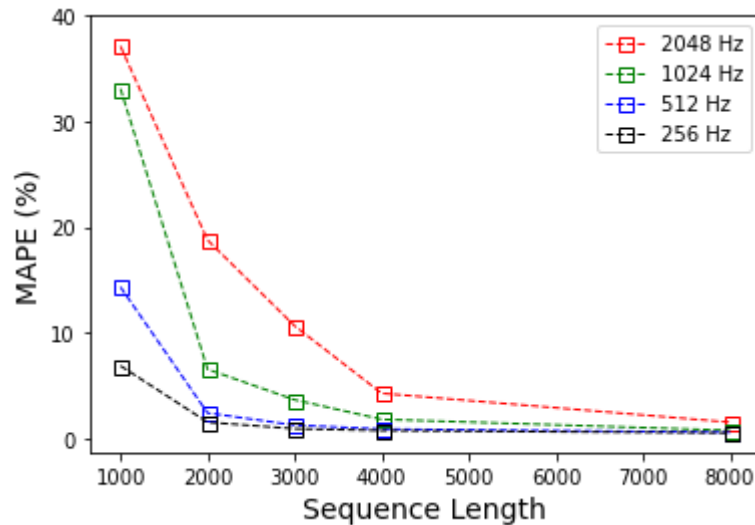


Capillary wicking



Bubble
release:
Verification
against
theory

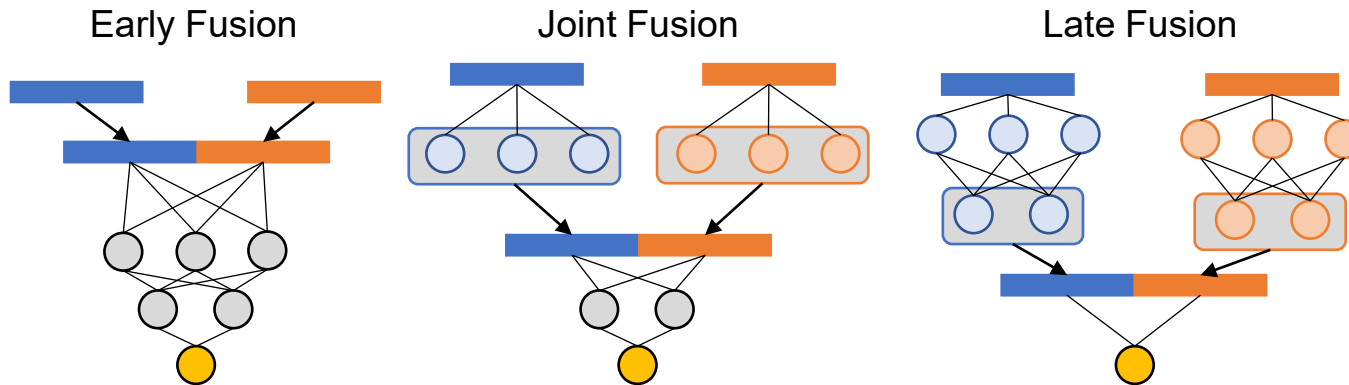
Effect of Temporal Length and Boiling Regime



- Prediction accuracy is determined by temporal length rather than sequence length (number of frames)
- The boiling regime affects boiling heat flux prediction accuracy.

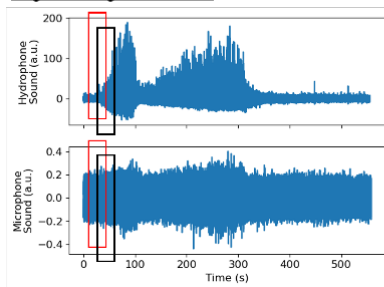
3. Multimodal Fusion for Heat Flux Measurement

Multimodal Acoustic Sensing and Data Fusion

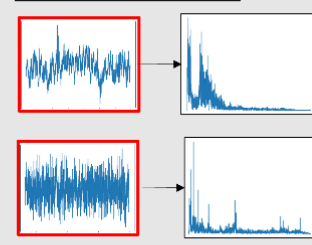


- Microphone: remote, noisy
- Hydrophone: immersion, clean

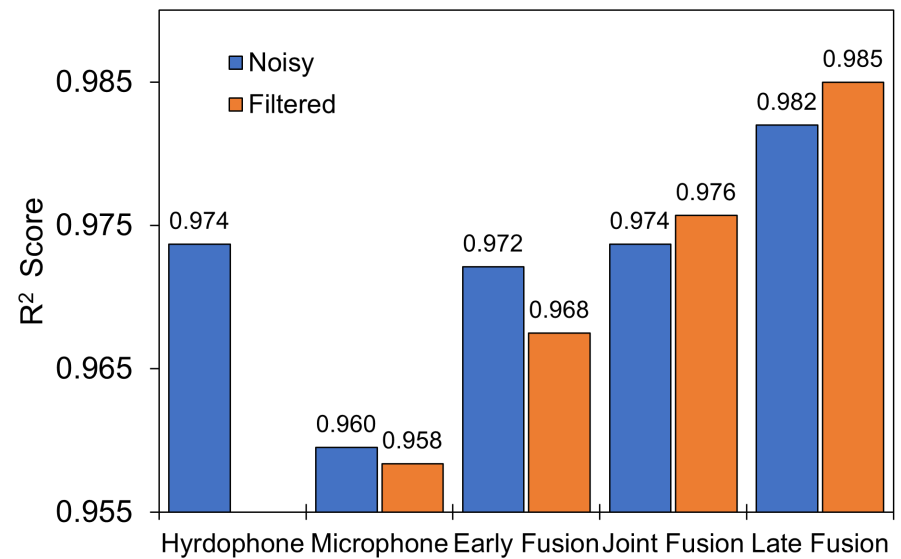
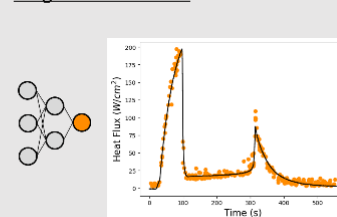
Signal Segmentation



FFT Feature Extraction

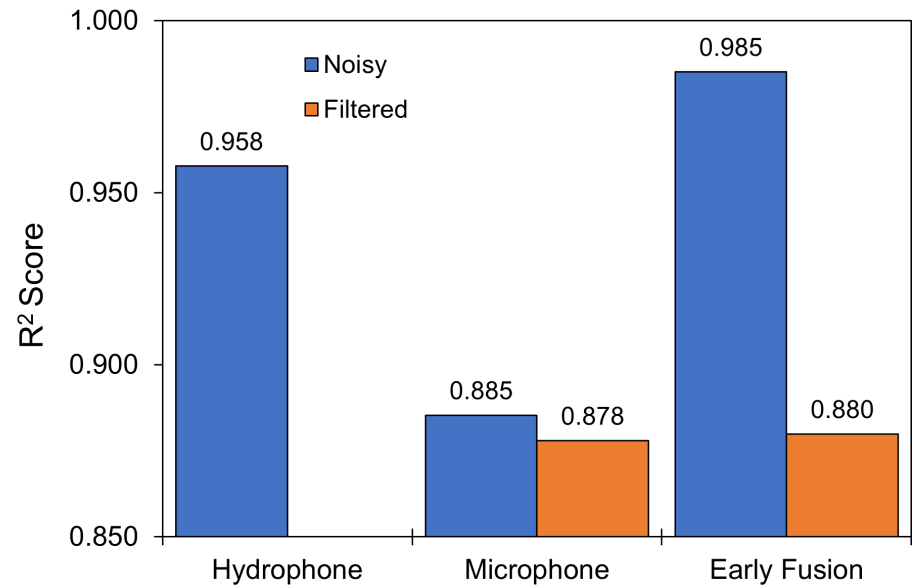
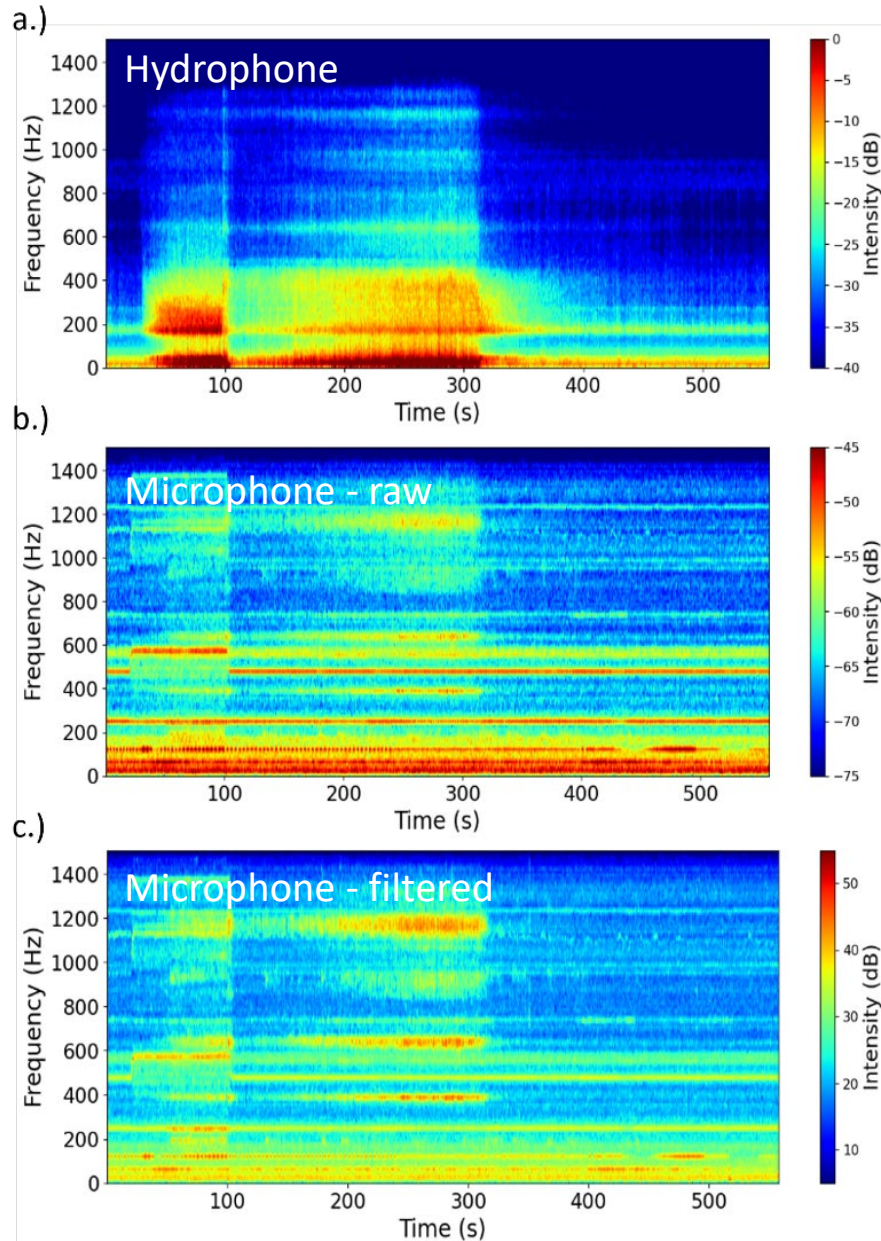


Regression Model

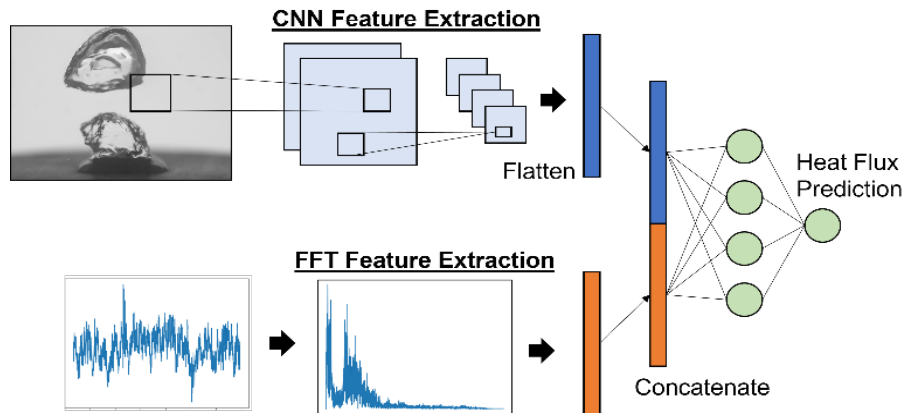


Effect of Denoising and Fusion on Heat Flux Measurements

Spectrogram of hydrophone, microphone (raw), and microphone (filtered).

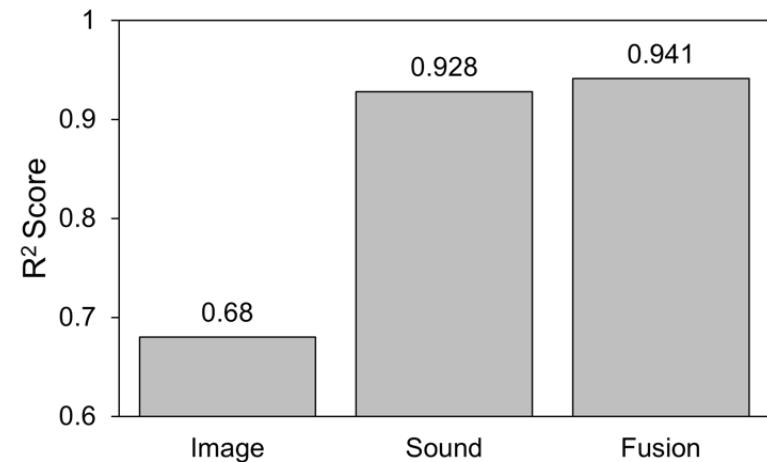
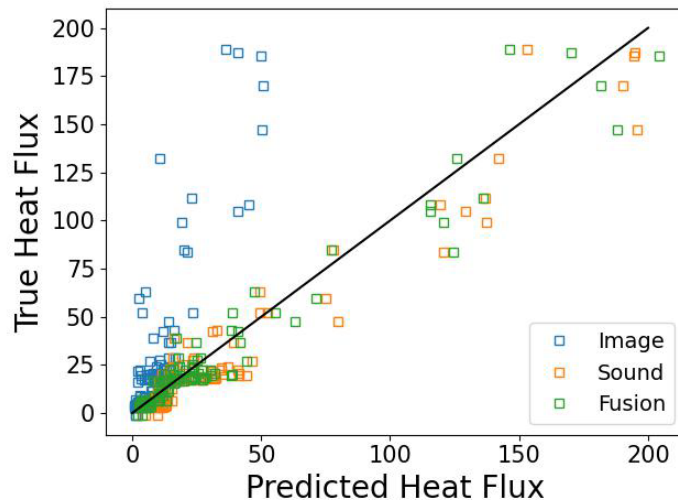


Audio-Video Fusion for Improved Prediction Accuracy



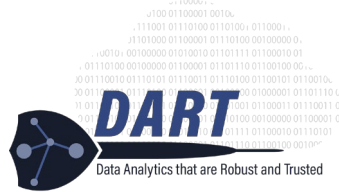
Audio-video fusion

- Static Image – CNN
- Acoustic sequence – FFT
- Fusion: concatenation



Acknowledgment

The machine learning work is supported by Arkansas NSF EPSCoR DART through AEDC Seed Grant # 22-EPS4-0028.



Computational resources by PSC and AHPCC through ACCESS and Neocortex program.



The experimental side of the work is supported by Arkansas NASA EPSCoR RID through ASGC and University of Arkansas Chancellors' Funds for Innovation and Collaboration, Commercialization, and GAP.



NSF and NASA I-Corps

NSF Regional I-Corps, Texas State I-Corps Site for Entrepreneurship

- Entrepreneurial Lead (EL): Hari Pandey (ART)
- Date: 10/14/2021 – 11/4/2021
- Interviews completed: 27



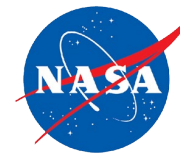
NSF National I-Corps, VentureWell

- EL: Hari Pandey (ART)
- Date: 3/14/2022 – 4/26/2022
- Interviews completed: 102



NASA I-Corps Short Course, NSF I-Corps Hub Southwest

- EL: Najee Stubbs & Christy Dunlap (AcoustiFlux)
- Date: 4/28/2023 – 5/26/2023



Ms. Catherine Corley served as the I-Corps Mentor for both teams



Selected Interviewee Affiliations



Global Cooling Technology Group



What we did and what we found?

Advanced
Cooling

CoolIT
systems™



Manufacturing/
industries



Vehicles



Integrated
Circuits/
Electronics



OZIC

Qualcomm

“Thermal failures occurs due to discrepancies in flow rates, system oversize, and cooling capacity”
- Marc (Liquid immersion specialists)

“Industry look at the practicality of solutions with structural integrity”
- Hamed (Senior thermal engineer)

“Non-intrusive methods could be important way for thermal monitoring in future”
- Shoaib (Senior research engineer)

“Non-intrusive methods would be great but need to make sure it checks temperature precisely”
- Balaji (Senior electronic design engineer)

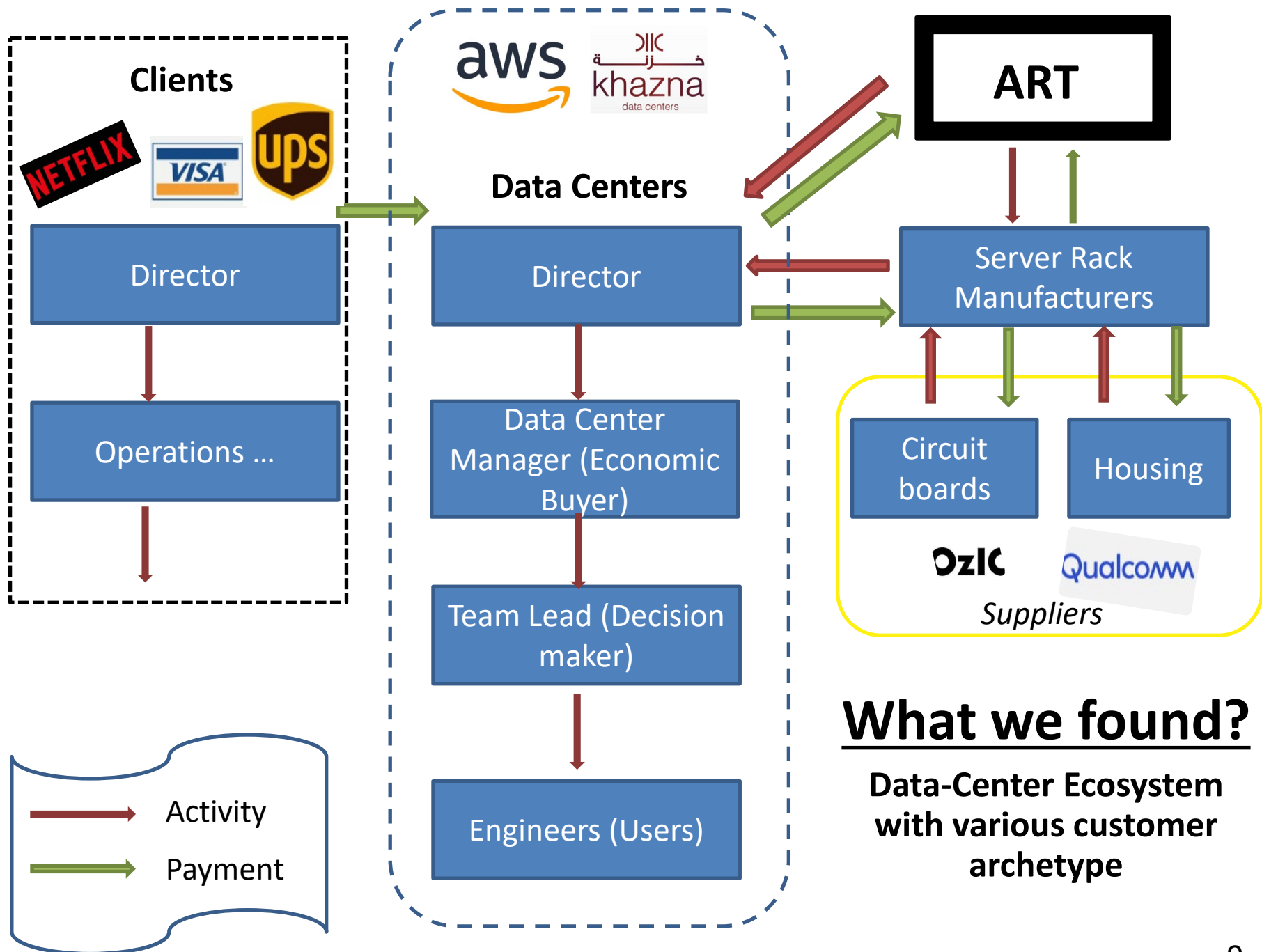
“Electronics working on extreme environments need better thermal control”
- John (CEO)

Finally!!!



Enoch: Google's data centers have their dedicated electrical power distribution system with transformers. High-voltage transformers are effective to reduce power loss and improve PUE

Fred: Data centers watch closely on power consumption rates and usage effectiveness. The prevalent of power related outages has increased industry's concern over real-time monitoring of power distribution and electrical systems.



Business Model Canvas

Key Partners



- Establish partnerships with key players in AE sensors field like MISTRAS

Key Activities



- Provide faster monitoring and feedback compared to typical available systems.
- Provide an easier way of replacing sensors than traditional sensors.

Key Resources



- Intellectual property
- MISTRAS Acoustic sensing and DAQ system
- Immersion cooling facility

Value Proposition



- Safe operation of data centers in extreme environments
- Reduce PUE by more than 30%.

Customer Relationships



- Get: Speak at technical conferences, publish white papers
- Keep: Provide webinars focusing on customer's events
- and monthly status update on technology
- Grow: Co-creation

Channels



- Direct Channel
- OEM channel

Customer Segments



1. Senior Research Engineer (Decision-Maker)
2. Data center Manager (Economic Buyer)
3. Thermal Engineers (User)

Cost Structure



- Materials and R & D cost for the development of prototype
- After successful testing, costs comprise of labor, marketing, and materials of the product.

Revenue Streams



- Asset sale: Acquisition by datacenters

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Heartland Challenge Startup Competition



Arkansas Governor's Cup Collegiate Business Plan Competition



Acknowledgment – Students and Collaborators



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- Robert Coridan, University of Arkansas (DART Seed Grant Recipient)
- Jeff Pummill, AHPCC
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Publications Acknowledging DART Seed Grant

Journal articles (2):

- C. Dunlap, H. Pandey, E. Weems, and H. Hu, “Nonintrusive Heat Flux Quantification Using Acoustic Emissions During Pool Boiling,” 120558, 2023.
- C. Dunlap, S. Featherstone, M. Smith, M. Vu, A. Williams, J. Bailey, and H. Hu, “Design and Fabrication of A Low-Cost and Programmable Dip Coating Machine,” HardwareX, 12, e00364, 2022.

Conference proceedings (8):

- Y. Xu, B. Zhao, S. Tung, and H. Hu, “Infusing Data Science into Mechanical Engineering Curriculum with Course-Specific Machine Learning Modules,” in 2023 ASEE Annual Conference, Jun 2023, Baltimore, MD, 38680.
- S. Pierson, N. Nawar, and H. Hu, “Comparing the Heat Removal Efficiency of Microchannel Heat Sinks Produced by CNC Milling Versus Powder Bed Fusion” in ASTFE 8th Thermal and Fluids Engineering Conference, TFEC-2023-45992.
- H. Hu and C. Heo, “Integration of Data Science into Thermal-Fluids Engineering Education”, in Proceedings of the ASME 2022 International Mechanical Engineering Congress and Exposition, Oct – Nov 2022, Columbus, OH, IMECE2022-88193.
- C. Dunlap, H. Pandey, and H. Hu, “Supervised and Unsupervised Learning Models for Detection of Critical Heat Flux During Pool Boiling,” in Proceedings of the ASME 2022 heat Transfer Summer Conference, HT2022-85582.
- H. Pandey, W. Waldo, and H. Hu, “Non-Intrusive Cooling System Fault Detection and Diagnostics Using Acoustic Emission,” in Proceedings of the ASME 2022 heat Transfer Summer Conference, HT2022-85429.
- J. Marsh, C. Dunlap, S. Pierson, and H. Hu, “Introducing LabVIEW and Arduino as Data Acquisition System Alternatives,” in 2022 ASEE Midwest Section Conference, Sep 2022, Tulsa, OK, 3279.
- C. Dunlap, J. Pummill, and H. Hu, “Infusing High-Performance Computing and Machine Learning in Mechanical Engineering Education,” in 2022 ASEE Midwest Section Conference, Sep 2022, Tulsa, OK, 2944.
- S. Pierson, J. Goss, and H. Hu, “Enhancing Undergraduate Mechanical Engineering Education with CAM and CNC Machining,” in 2022 ASEE Midwest Section Conference, Sep 2022, Tulsa, OK, 6932.