Supervised by
Dr. AJ Perez

Customized for **MIT Office of Innovation**

Weather Forecasting

Statistical and AI Models for Real-Time Forecasting on the Edge

Office of Innovation | MIx
December 10th, 2025

MIT Team

6 MIT students with requisite computer science, aerospace, engineering, and industry experience

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Frederick, MD

Executive Summary

A. **Fast, accurate, local weather forecasts** for operational decision-making.

B. **Improve severe weather warnings** using real-time sensor data and edge ML.

C. Forecast point-level conditions from multi-year meteorological data and test **models optimized for edge deployment**.

D. Completed model comparisons on **accuracy and efficiency**, aiming for **operational deployment**.

E. Currently collecting preliminary **results to guide future work** and model building.

Deploy edge ML models to deliver actionable, point-level weather forecasts.

Agenda

Project Goal & Background

Literature Review

Model Testing and Comparison (Experiment)

Conclusions & Future Work

Insufficient Local Forecasting Leads to Preventable Storm Damage

[1] The Independent. “Timelapse shows Texas flash floods turn dry river into deadly rapids in 20 minutes.” YouTube, 28 Nov. 2024, https://www.youtube.com/watch?v=cOxh8hwAN3I

Insufficient Local Forecasting Leads to Preventable Storm Damage

$1.74 trillion

Total **economic losses from natural disasters** in the U.S. in the last 15 years

[2] NOAA National Centers for Environmental Information (NCEI). "U.S. Billion-Dollar Weather and Climate Disasters (2025)." https://www.ncei.noaa.gov/access/billions/

Our Mission & Research Focus is an Efficient Weather Nowcasting System

We want to develop an **edge-deployable**, **micro-scale** weather-forecasting system that delivers **real-time**, **location-specific** predictions.

Optimize models for edge devices

Enable real-time micro-forecast alerts

Improve accuracy with sensor fusion

Best architecture for fast inference

Our Edge-Based Forecasting Pipeline Compresses Full Weather Stack

Edge Sensors	Pre - Processing	Forecast Model	Local Prediction	Fast Alerts
→ Collect real-time, point-level weather data.	→ Clean and normalize raw signals.	→ Predict next hours from past data.	→ Compute forecasts directly on-device.	→ Trigger immediate, actionable warnings.
→ Capture local atmospheric conditions.	→ Fuse multiple sensor inputs.	→ Run light, optimized architecture.	→ Coordinate - specific outputs offline.	→ Support rapid protective decisions.

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We Organized our Literature Review into 6 Topics

Meteorology

Physics of the atmosphere: precipitation, storms, and weather processes

Data & Assimilation

Where weather data comes from and how models ingest observations in real time

Sensor Integration

Methods for fusing diverse, high-dimensional sensor data

Traditional Forecasting

Structure of numerical and statistical weather models

ML Forecasting

Types of ML models, their performance, and active research directions

Edge Computing

How forecasting models are optimized for low-power, edge devices

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Sensor Integration

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Nowcasting!
Rain, thunderstorms, hurricanes, fog, fires, and tornadoes.

Traditional Forecasting

Structure of numerical and statistical weather models

ML Forecasting

Types of ML models, their performance, and active research directions

Edge Computing

How forecasting models are optimized for low-power, edge devices

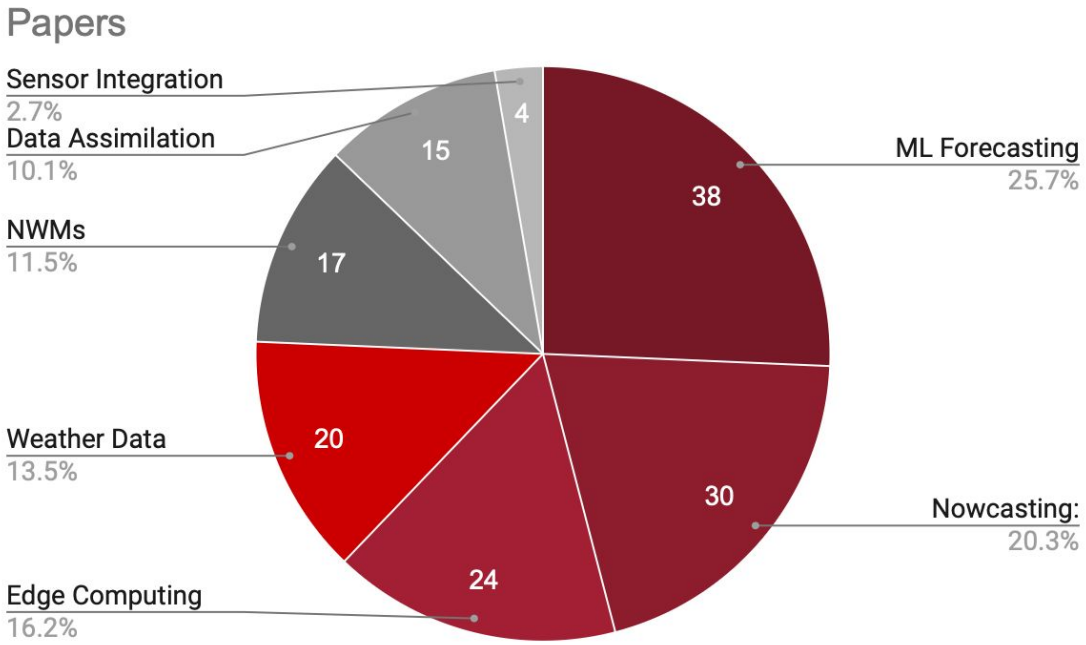
148 References Across 7 Key Topics Inform Opportunity Areas of Future Work

7 Topics

148 Sources

205 PowerPoint Slides

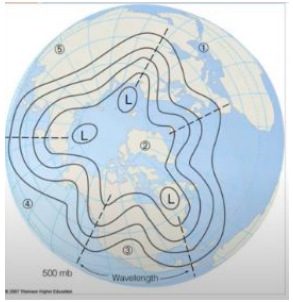
Literature reveals need for ML forecasting and nowcasting.



Meteorology
Literature Review

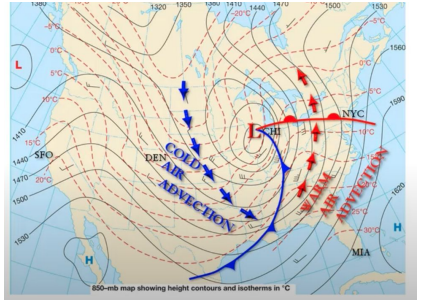
The Atmosphere is Modeled as a 3 Layer River [3]

Level 1 (20k ft+)



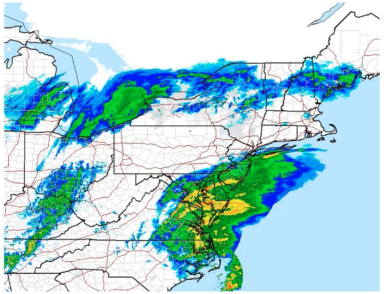
Global Jet Streams

Level 2 (10-20k ft)



Temperature & Wind Speed

Level 3 (Surface-10k ft)



Precipitation & Nowcasting

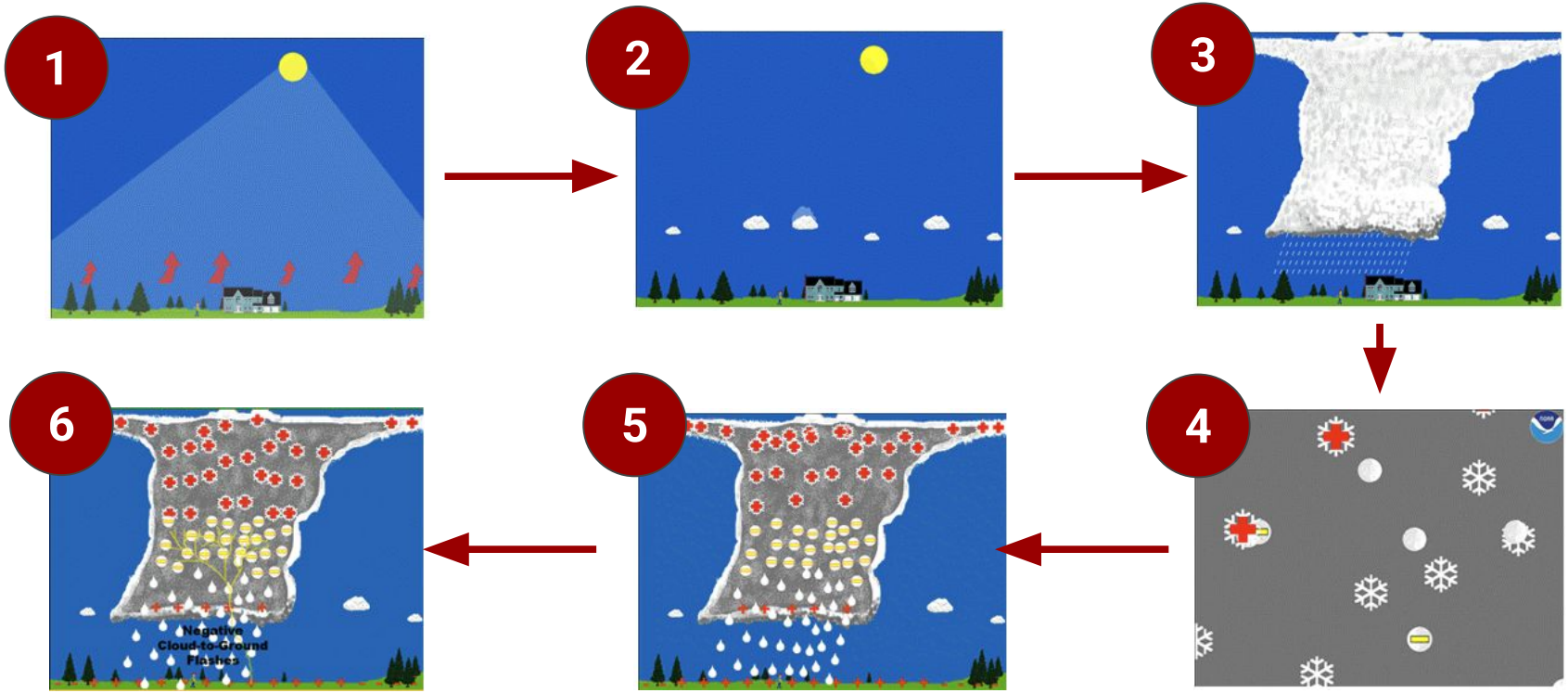
Governed by four fundamental equations [4]:

1. **Navier-Stokes** - describes wind and momentum
2. **Mass Continuity** - conserves air mass
3. **Thermodynamics** - heat and energy transfer
4. **Ideal Gas Law** - pressure, temperature, & density

[3] "Introduction to Weather Forecasting." YouTube, YouTube, www.youtube.com/watch?v=lUqmsjpfz3c. Accessed 22 Sept. 2025.

[4] Bauer, P., Thorpe, A. & Brunet, G. The quiet revolution of numerical weather prediction. *Nature* 525, 47–55 (2015). https://doi.org/10.1038/nature14956

Case Study: Understanding Lightning Science Through NWS Visualization [5]



[5] National Weather Service. "Understanding Lightning Science." National Weather Service, U.S. Department of Commerce, www.weather.gov/safety/lightning-science-overview. Accessed 4 Oct. 2025.

Data Assimilation & Sensor Integration

Literature Review

NOAA's Five Methods for Collecting Atmospheric Data [6]

Weather Balloons

Twice-daily profiles of pressure, temperature, humidity, and wind

Aircraft Reports (AMDAR)

Automated wind and temperature data from commercial flights

ASOS

900+ automated surface stations providing minute-by-minute weather data

Buoys

Coastal/offshore sensors measuring waves, pressure, and sea-surface temperature

Remote Sensing

Satellite and radar observations covering areas without ground instruments

[6] National Weather Service. "NOAA Observation Systems." Weather.gov, U.S. Department of Commerce, https://www.weather.gov/about/observation-equipment. Accessed 20 Sept. 2025.

Data Fusion Pipeline: Processing Raw Inputs Into a Data Structure Ready For Models [7]

1. Raw Inputs

Radar Satellite Surface

Radar: Reflectivity (Z) & Rain Rate

Satellite: Cloud tops (IR/ Visible)

Surface Stations: Wind, Pressure, Temp

2. The "Grinder"

Alignment: Resampling to shared grid & syncing timestamps

Normalization: Scaling disparate values (e.g., Pressure vs. Rain)

Masking: Handling missing sensor data

3. Fused Tensor

Technique: Channel Concatenation (Stacking)

Structure: Multi-dimensional array

Result: Unified input ready for models

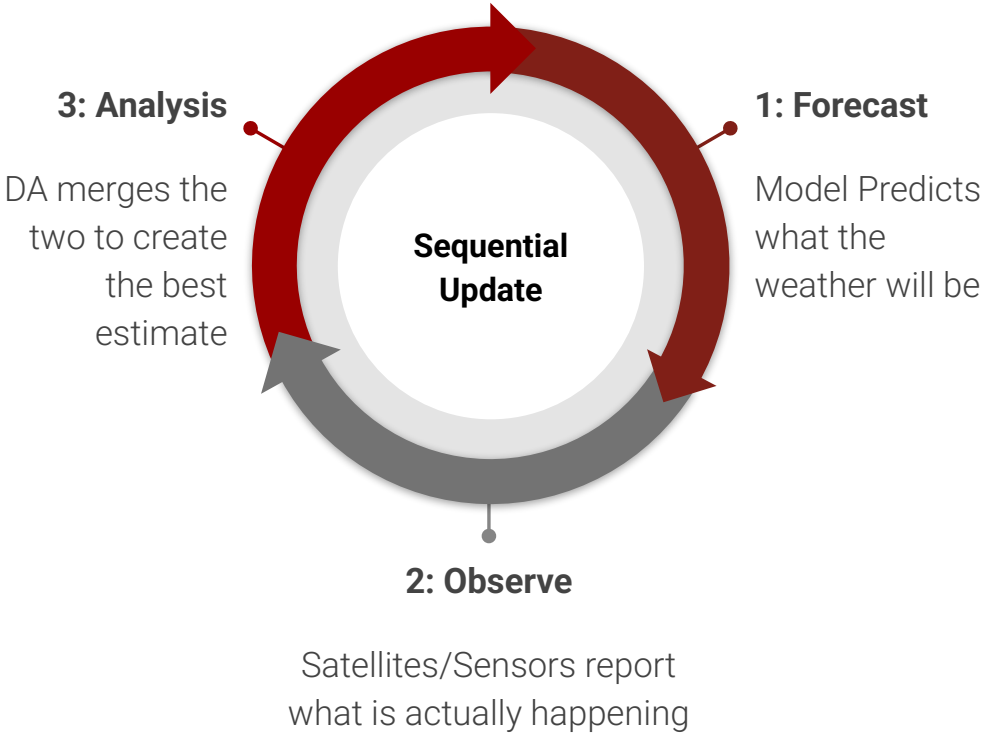
[7] An, Sojung, et al. "Deep Learning for Precipitation Nowcasting: A Survey from the Perspective of Time Series Forecasting." Arxiv.Org, 10 June 2024.

Data Assimilation: Correcting Model Errors With Real-Time Observations [8]

Goal:
Merge real-world observations with physics models to create accurate initial conditions

Problem:
Initial errors explode over time

Solution:
Sequential updating - constantly correcting model's trajectory with new sensor data



[8] Pandya, Dishant, Bhasha Vachharajani, and Rohit Srivastava. "A Review of Data Assimilation Techniques: Applications in Engineering and Agriculture." Materials Today: Proceedings, vol. 62, part 13, 2022, pp. 7048–7052. Elsevier, https://doi.org/10.1016/j.matpr.2022.01.122.

Forecasting
Literature Review

Numerical Weather Prediction: The Physics Based Foundation of Modern Forecasting [9]

1. Discretize

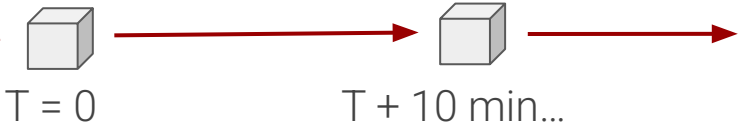
Slicing atmosphere into millions of 3D boxes

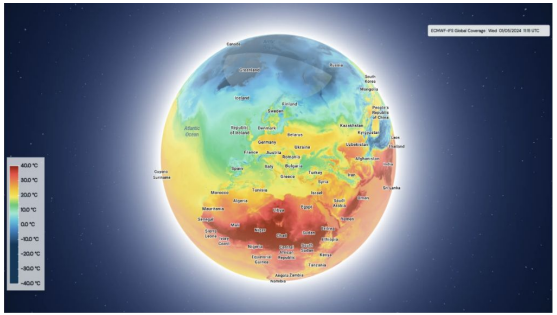
2. Parameterize

Atmospheric parameters calculated for each grid point using physics equations

3. Visualize

Visualization for ECMWF global coverage for temperature





[9] "What is numerical weather prediction?". meteomatics. (2024, June 11). https://www.meteomatics.com/en/weather-model-europe/what-is-numerical-weather-prediction/

Overview of Traditional NWP Models By Scale [10]

Global

- ➔ Models: GFS (NOAA), ECMWF (Euro)
- ➔ Update Cycle: Slow (Every 6-12 hours)
- ➔ Role: Large-scale patterns up to 10+ days

Mesoscale

- ➔ Models: HRRR (US), NAM (N. America)
- ➔ Update Cycle: Hourly
- ➔ Role: Captures convection (thunderstorms), terrain flows, and aviation hazards

Microscale

- ➔ Target: Neighborhood/City/Runway scale
- ➔ Problem: Traditional NWMs are too computationally expensive
- ➔ Opportunity: Explore machine learning techniques

[10] Climavision. The Ultimate Guide to Weather Forecast Models 2025. Climavision, 2025, https://climavision.com/resources/the-ultimate-guide-to-weather-forecast-models-2025/.

Overview of Current ML Models Exposes the Computational Limits of Larger Architectures

Global Giants [11]

Models: GraphCast, Pangu-Weather, FourCastNet

How it works: Trained on decades of global reanalysis data (ERA 5)

Pros: 10,000x faster than traditional NWPs

Cons: Needs large GPU/TPU clusters

Deep Nowcasters

Models: ConvLSTM [12], DGMR [13], MetNet [14]

How it works: Learns storm evolution from radar imagery

Pros: Detailed rain/convective forecasts

Cons: Computationally heavy; can blur outputs

Edge Contenders [15]

Models: Random Forest, ARIMA, Kalman Filter, SVM…

How it works: Maps sensor inputs -> short-term forecast

Pros: Fast, low-power, edge friendly

Explore Here!

[11] Pasche, Olivier C., et al. Validating Deep-Learning Weather Forecast Models on Recent High-Impact Extreme Events. 26 Apr. 2024, https://arxiv.org/abs/2404.17652
[12] "What Is Convolutional Long Short-Term Memory (CONVLSTM): Ai Basics: Ai Online Course." Www.Aionlinecourse.Com, www.aionlinecourse.com/ai-basics/convolutional-long-short-term-memory-convlstm. Accessed 05 Oct. 2025.
[13] Ravuri, Suman, et al. "Skilful Precipitation Nowcasting Using Deep Generative Models of Radar." *Nature News*, Nature Publishing Group, 29 Sept. 2021, www.nature.com/articles/s41586-021-03854-z. Accessed 27 Sept. 2025.
[14] Espeholt, Lasse, et al. "Deep Learning for Twelve Hour Precipitation Forecasts." *Nature News*, Nature Publishing Group, 1 Sept. 2022, www.nature.com/articles/s41467-022-32483-x?utm_source. Accessed 05 Oct. 2025.
[15. Kumar, Rajesh, and Anjali Sharma. "Edge AI: A Review of Machine Learning Models for Resource-Constrained Devices." Artificial Intelligence and Machine Learning Review, Scipublication, Mar. 2025.

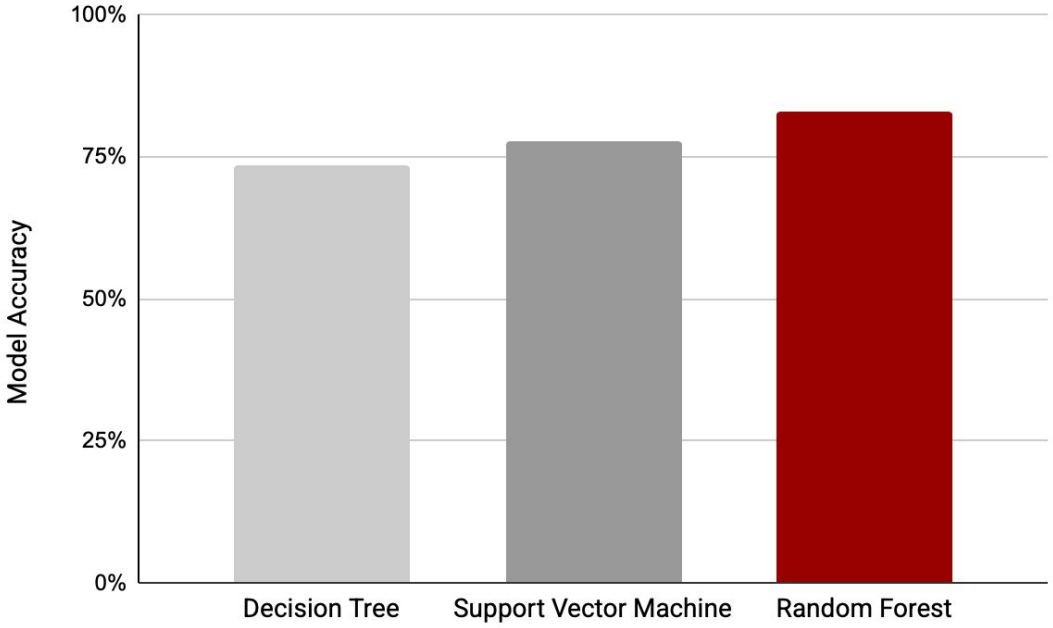
Case Study: Random Forest Outperforms Other Edge Contenders in Classification [16]

Inputs:

- ➔ 7 Historical Variables: Temp, Humidit Rainfall, Wind, Pressure, Solar Radiation
- ➔ Preprocessing: Data cleared to remove noise and missing values

Outputs

- ➔ Classified daily weather into five categories: Sun, Rain, Drizzle, Fog, Snow



[16] Joyarieb, Pedro, et al. "Comprehensive Approach to Weather Prediction with the Random Forest Algorithm." Data Science Insights, vol. 3, no. 2, 7 Aug. 2025, pp. 75-81.

Edge Computing
Literature Review

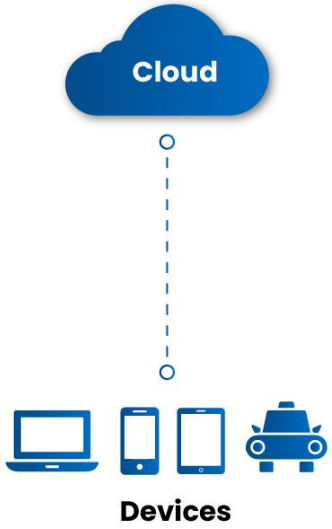
Edge Computing Allows Analysis Without Cloud Dependency [17]

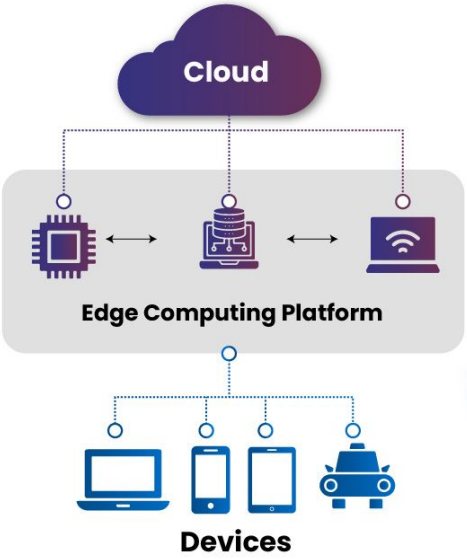
Core Concept: move computation away from centralized servers and places it closer to data source

Goal: process data locally to enable real-time analysis without relying on distant data centers

Benefits:

- ➔ Reduced Latency
- ➔ Bandwidth Efficiency
- ➔ Server Load





[17] "What Is Edge Computing? | Benefits of the Edge." Cloudflare, www.cloudflare.com/learning/serverless/glossary/what-is-edge-computing/. Accessed 11 Oct. 2025.

Case Study: Achieving High Forecasting Accuracy On Edge Device [18]

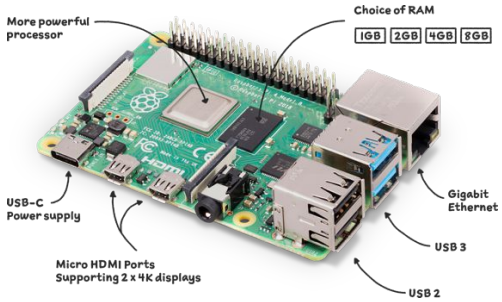
The Experiment:

The Hardware: Raspberry Pi 4 (Standard Edge Device)

The Model: Random Forest

The Inputs: Temperature & Humidity sensors

The Framework: TensorFlow Lite



The Results:

Accuracy: **91%**

Latency: **50** milliseconds

Outputs: Instant classification (Sunny vs. Rainy) + Temperature (Regression) predictions

[18] Ihwan, Muhammad Faiz Raihan. "AI/ML Integration on Edge Computing for More Accurate Weather Predictions." Journal of Computation Physics and Earth Science, vol. 2, no. 1, Apr. 2022, pp. 1-6, journal.physan.org/index.php/jocpes/article/view/28/27. Accessed 11 Oct. 2025.

Agenda

Project Goal & Background

Literature Review

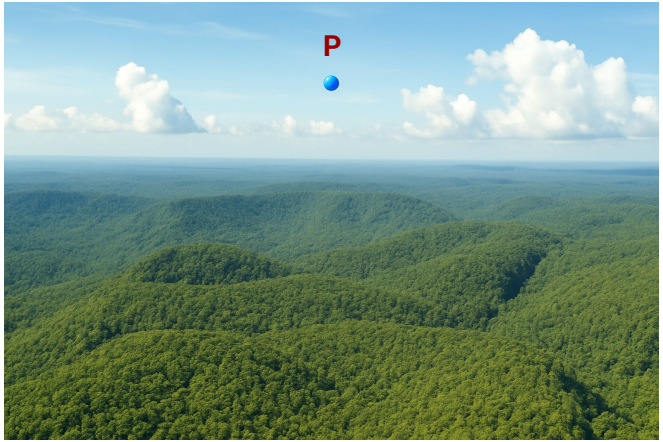
Model Testing and Comparison (Experiment)

Conclusions & Future Work

Experiment Objective: What models are best for real-time, local forecasting?

Model Task

Given last 24 hours of weather data at point P → Predict next 6 hours of weather data at point P



Experiment Objective: What models are best for real-time, local forecasting?

Model Task

For all P:

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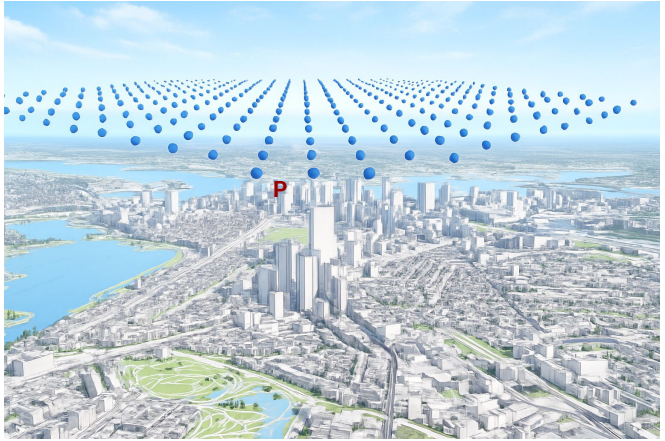


Experiment Design - Forecasting 6 Weather Variables at 49 Points Above Boston

Spatial Resolution and Coverage:

- **49 points** of data (7 by 7 grid, centered at MIT)
- Resolution roughly 10km
- Grid of points spans **3,300 km**

At each point, we have **hourly** data from **2015-2025**, on these 6 weather variables:

Temperature

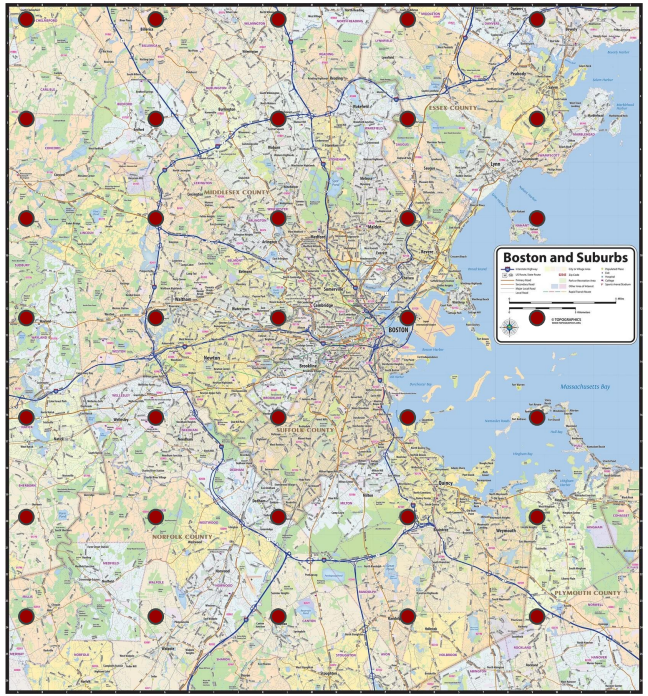
Wind Speed

Humidity

Pressure

Precipitation

Luminosity

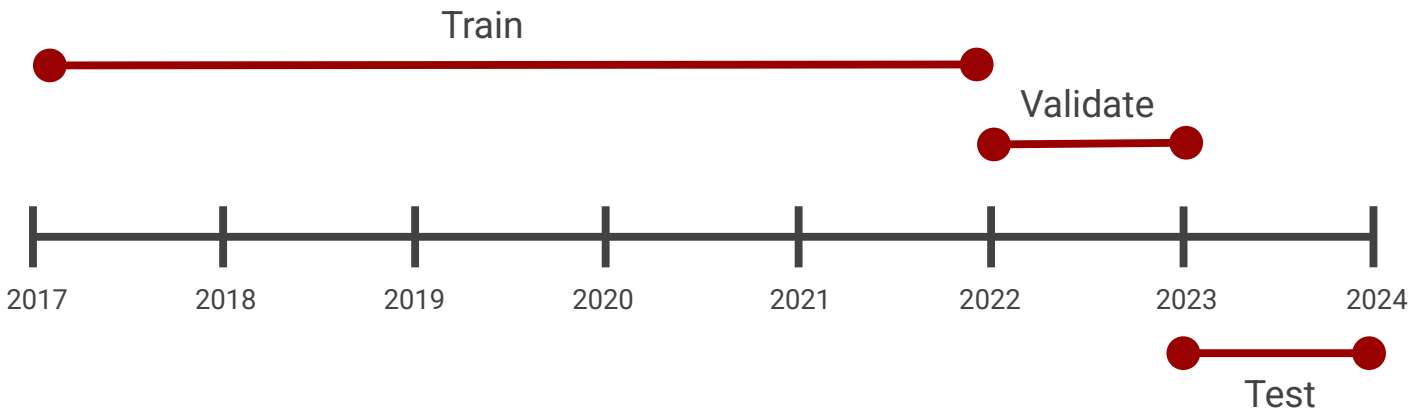


Data from ERA5-Land Data Set

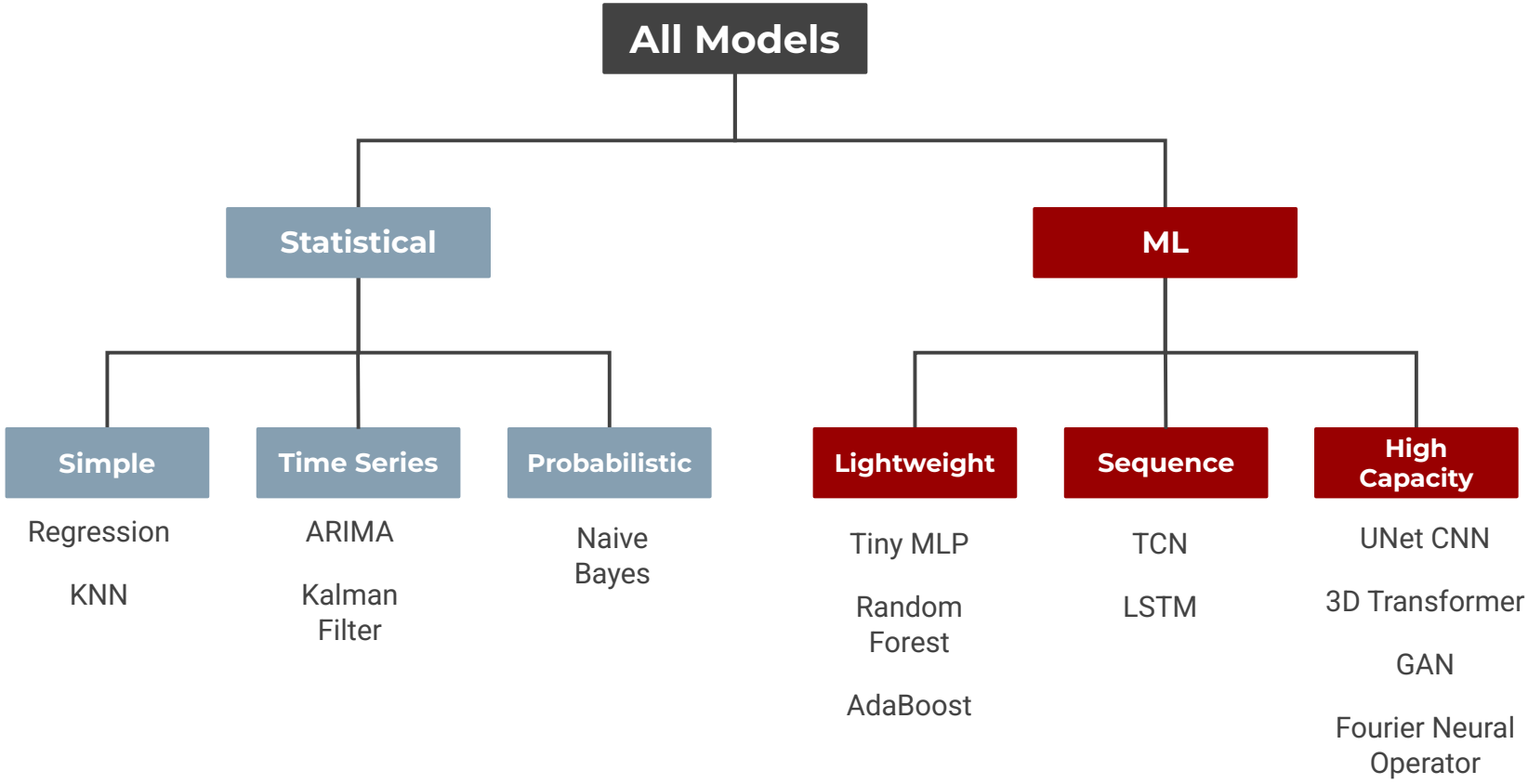
Experiment Design - Forecasting 6 Weather Variables at 49 Points Above Boston

Supervised Learning Flow:

1. Split training data into supervised pairs and train a model using gradient descent
2. Use validation data to choose optimal hyperparameters
3. At each hour in the test set, predict next 6 hours, and compute root mean squared error using true values



Experiment Design - Model Downselection from 20+ Models to 7 Light & Temporal



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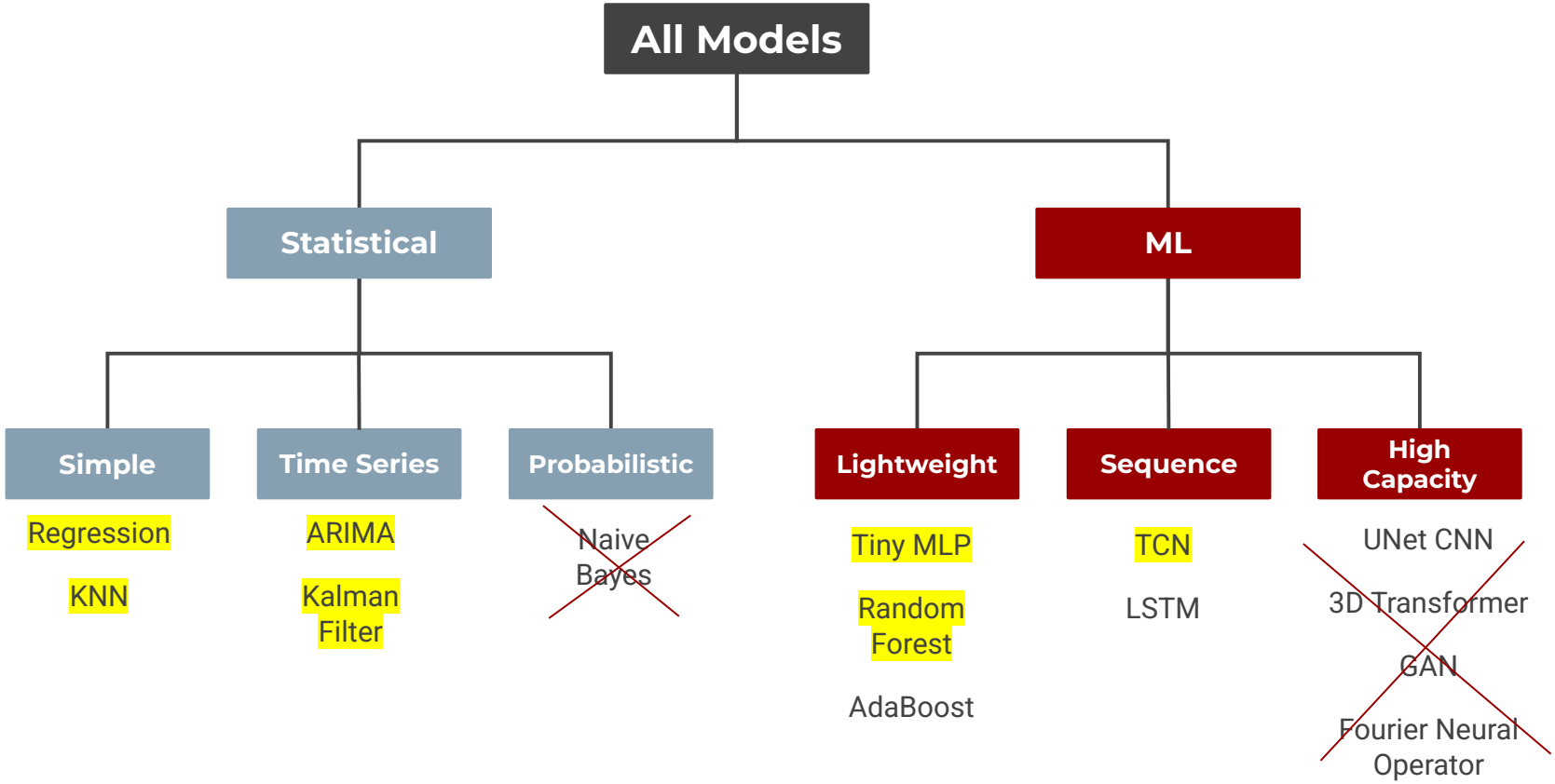
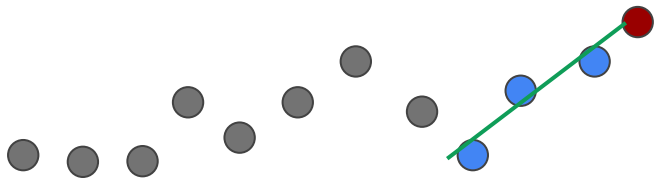
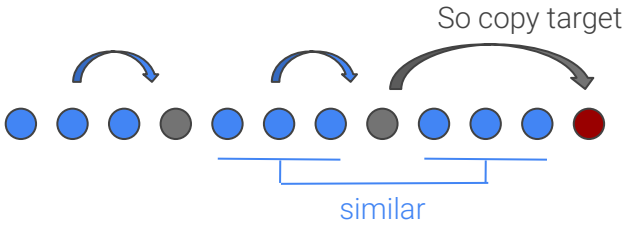


Experiment Design - Downselected to 4 Best Statistical Models

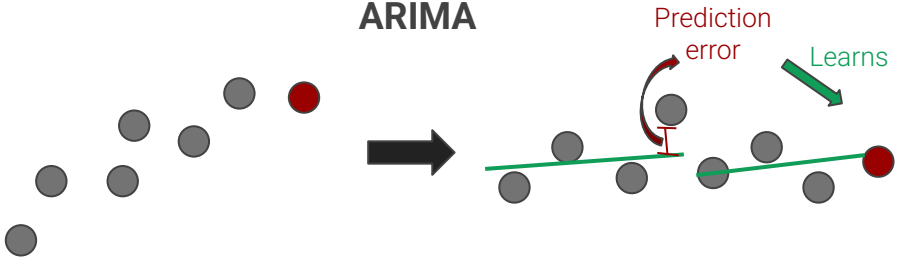
Regression



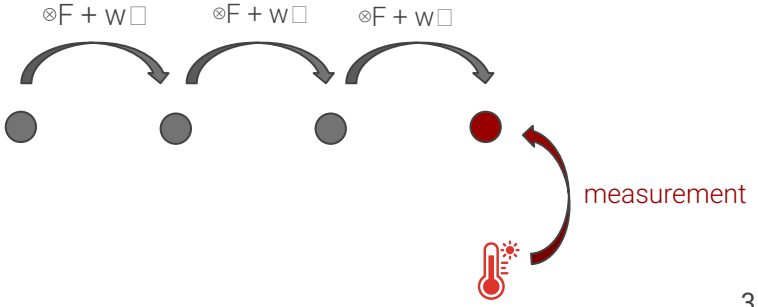
KNN



ARIMA

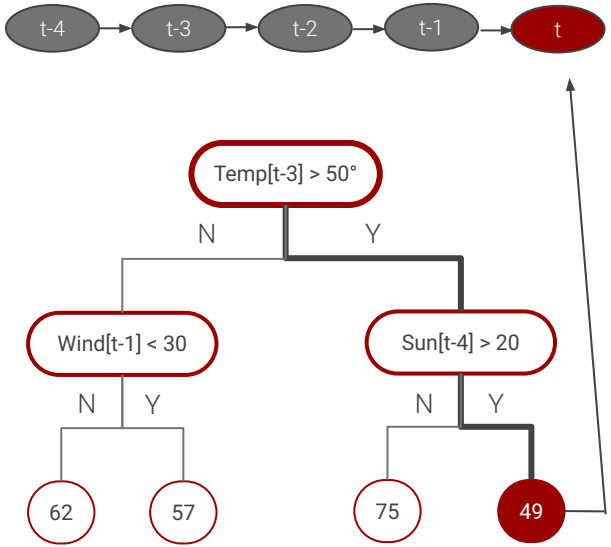


Kalman Filter

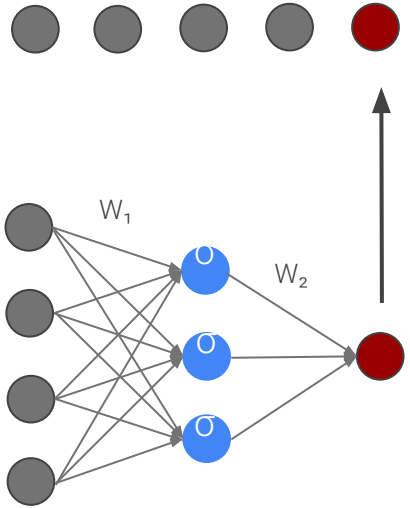


Experiment Design - Downselected to Best 3 ML Models

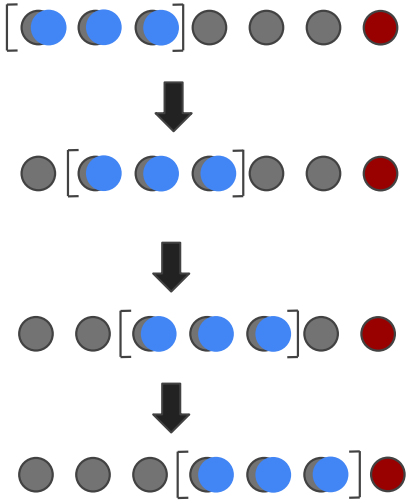
Random Forest



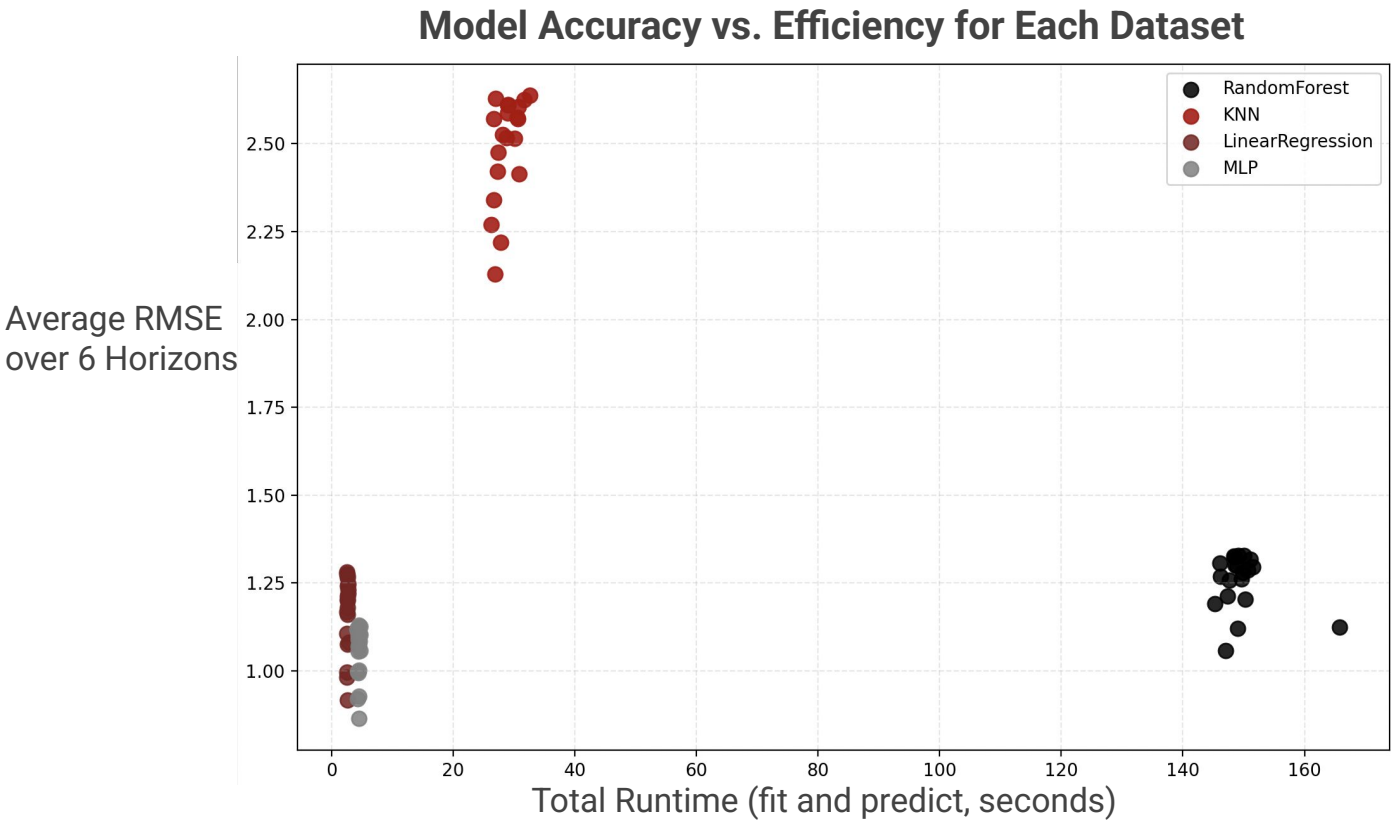
Tiny Multi-Layer Perceptron



Temporal Convolutional Network



Preliminary Results Indicate Regression, MLP Best at Temperature Prediction



Experiment = Proof of Concept for an Efficient Weather Nowcasting System

What is the humidity in 6 hours? Temperature in 2 hours? Wind speed in 3 hours? Need instant forecast.

Model's RMSE For Each Prediction Task

	Next Hour (T+1)		T + 2		T + 3	
	Temp	Rain	Temp	Rain	Temp	Rain
MLP	0.52	0.94	0.76	1.03	0.99	1.33
LR	0.41	1.62	0.77	2.24	1.09	2.67
RF	0.79	1.5	1.0	1.71	1.2	1.94

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Next Up → Integrate More Complicated Models into Our Experiment

Extend to spatial forecasting (graph neural networks to encode physics)

Build a transformer (suitable for edge compute - ex: sparse attention)

Test best models on real data for a specific AF use case

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C. Forecast point-level conditions from multi-year meteorological data and test **models optimized for edge deployment**.

D. Completed model comparisons on **accuracy and efficiency**, aiming for **operational deployment**.

E. Currently collecting preliminary **results to guide future work** and model building.

Deploy edge ML models to deliver actionable, point-level weather forecasts.

Thank you!

Appendix