WEATHER PREDICTION

GROUP 2

USING ML

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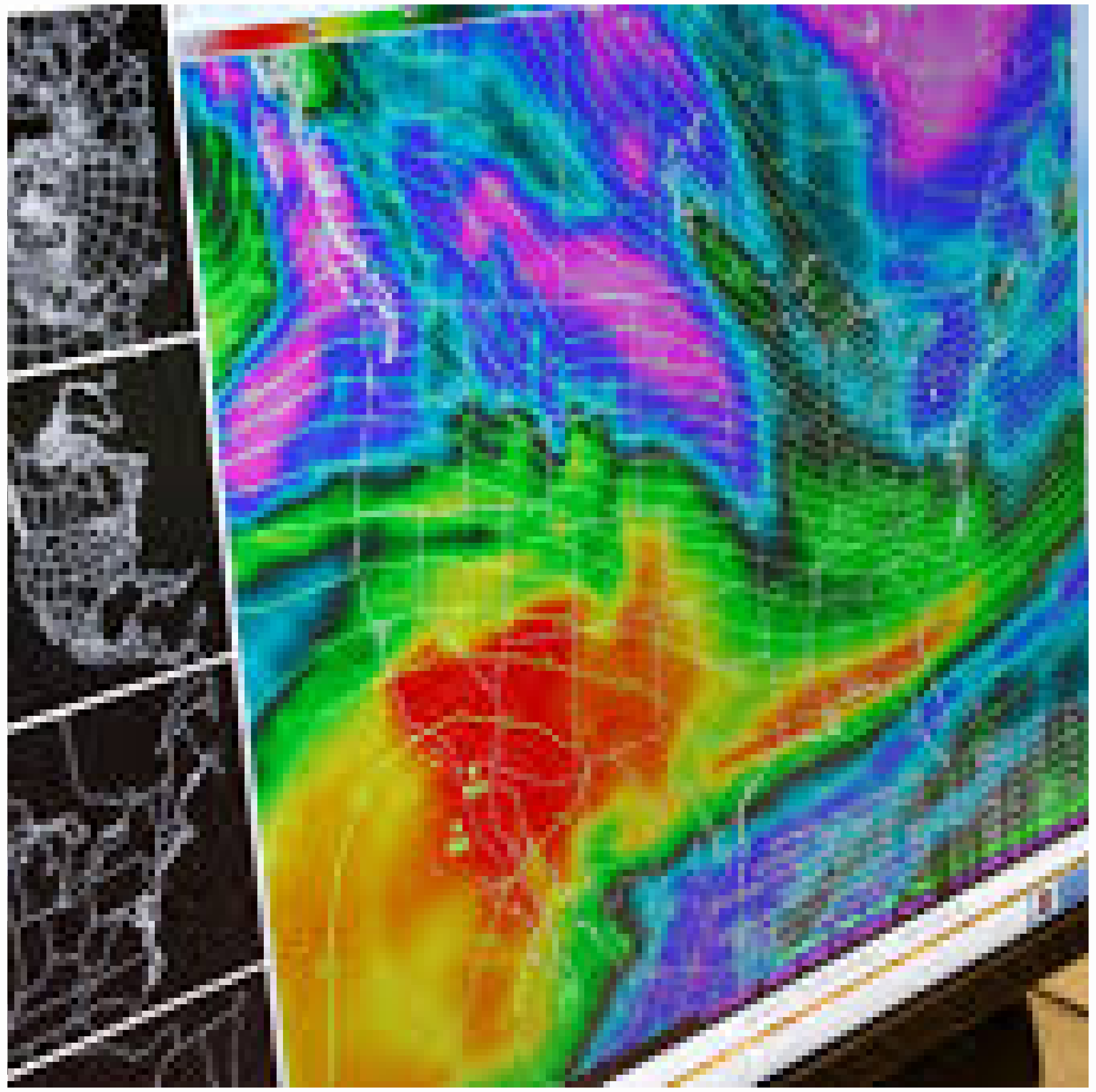
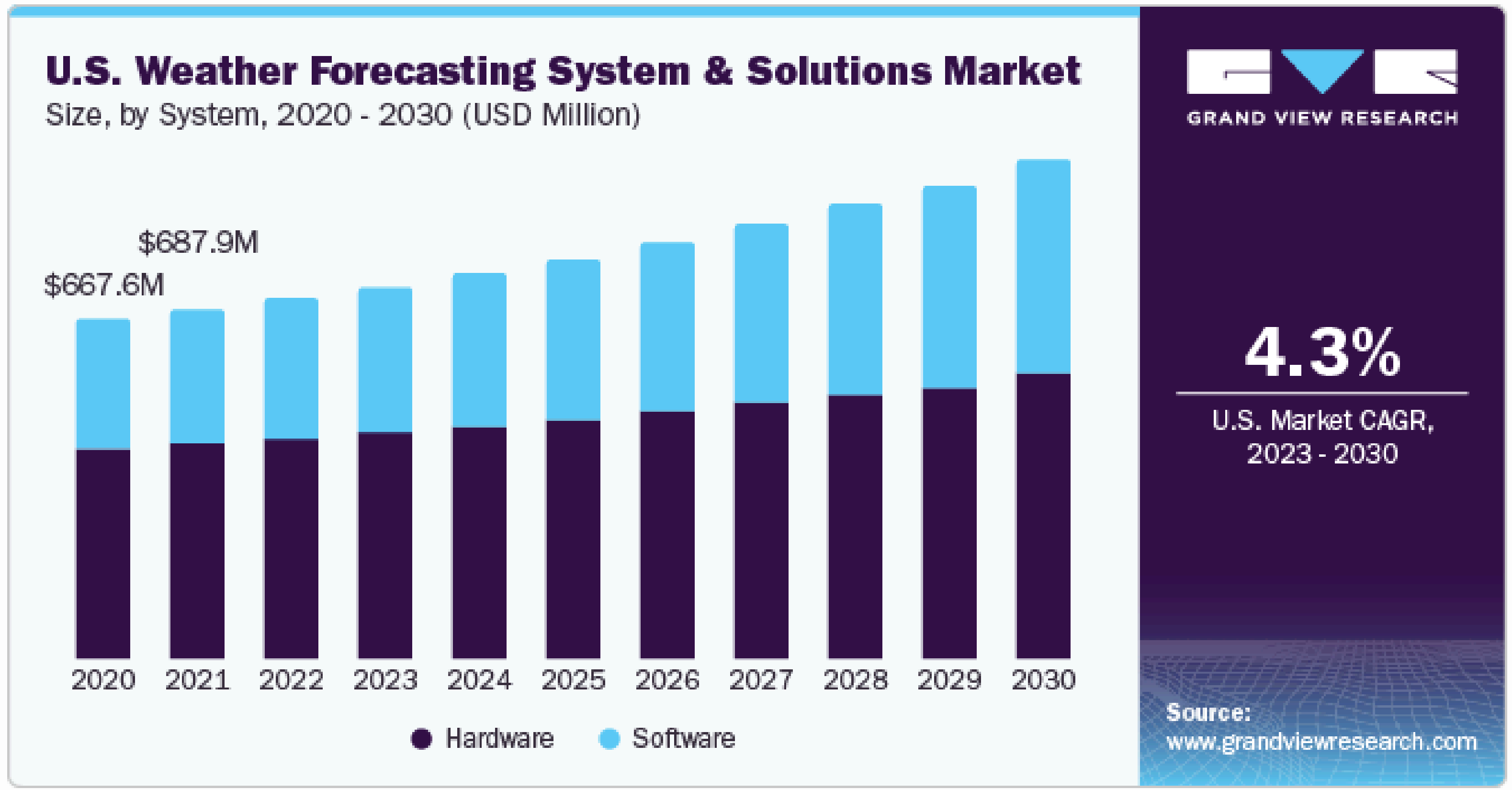


BACKGROUND

- Within the National Weather Service (NWS), relies on Numerical Weather Prediction (NWP) models.
- Use mathematical equations based on atmospheric physics to simulate and predict weather patterns.
- Have many challenges and limitations:
  - Limited understanding of physical mechanisms
  - Difficulties in extracting vast amounts of observational data
  - Require substantial computational resources

MARKET



Global Weather Forecasting System market size valued at **3.22 billion USD in 2022.**

Expected to grow at a compound annual growth rate of **6.6% from 2023 to 2030.**

Involved Companies: AIRMAR Technology Corporation, Campbell Scientific, Inc., and Lockheed Martin Corporation

DRAWBACKS

Limited Interpretability

Black-box nature of deep learning makes predictions hard to explain

High Computational Cost

Requires significant resources to process large datasets

Data Reliability Issues

Weather datasets often contain missing, inconsistent data.

Dependence on Historical Data

ML models rely on past weather patterns, which may not always reflect future conditions.

Climate change introduces new patterns that historical models may fail to capture.

PROBLEM

Lack of Standardized Datasets

There is no universally agreed-upon dataset for training and testing models, which could lead to differences in data sources and result in inconsistent model performance.

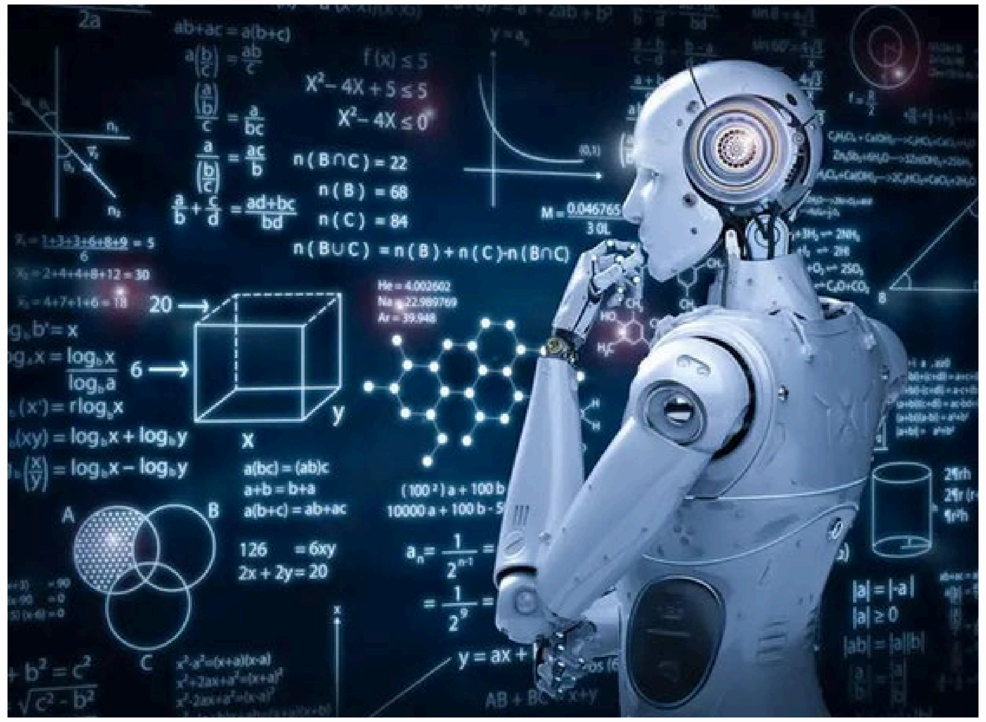
Lack of Domain-Specific AI Models

Many AI techniques are general-purpose and not optimized for meteorology

Overfitting to Past Weather Patterns

AI models may rely too heavily on historical trends and struggle with new, unseen conditions.

CHALLENGE TECHNIQUES



Data Limitations and Quality

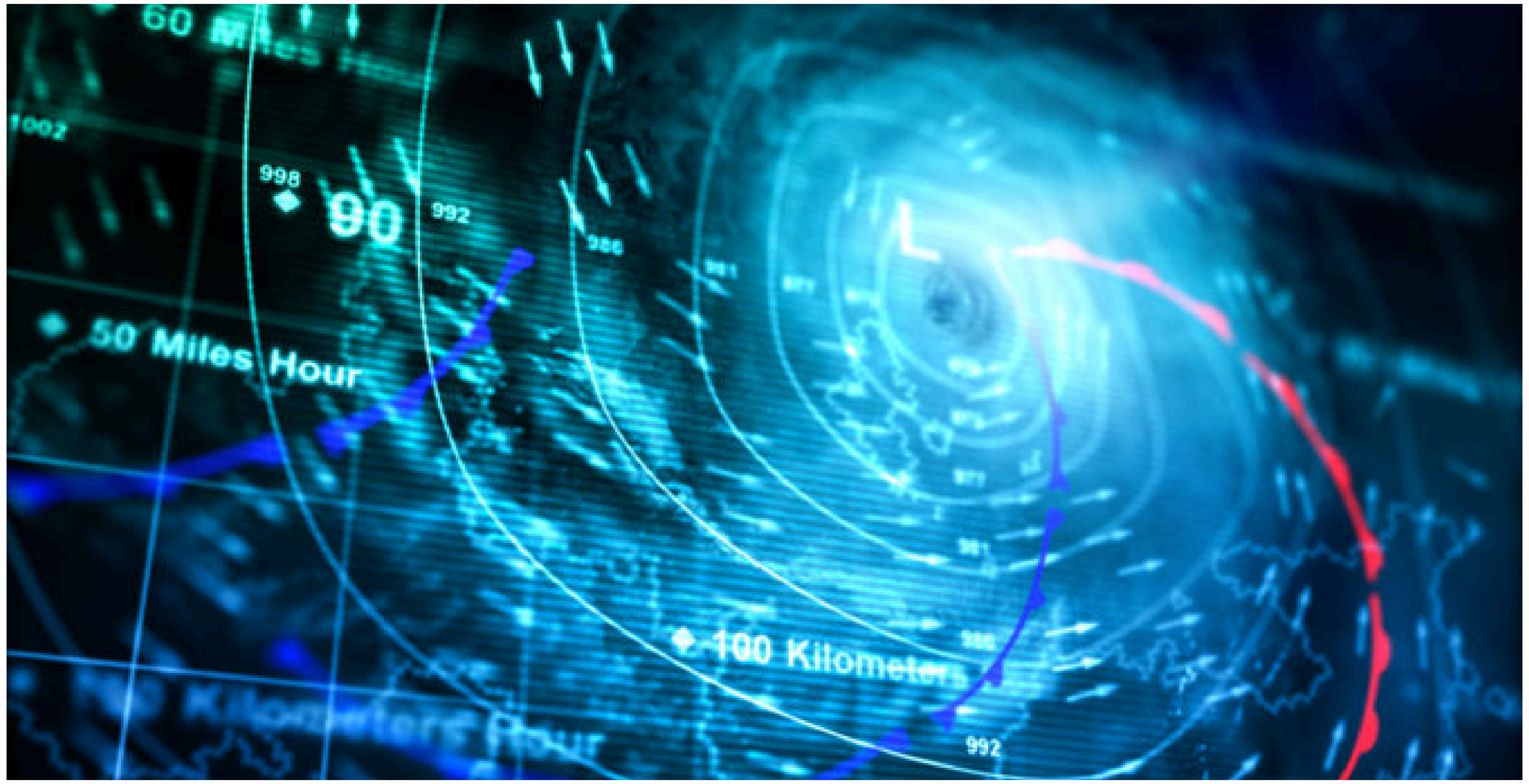
Lack of Explainability and Trustworthiness

Bridging the Gap Between Research and Operations

DATA LIMITATIONS

01 Successful ML development heavily relies on quality-controlled datasets. Challenges include gaps in observational data, rare weather events, limited data access, and coordination.

Furthermore, data bias and incompatibility can hinder the development and performance of ML models

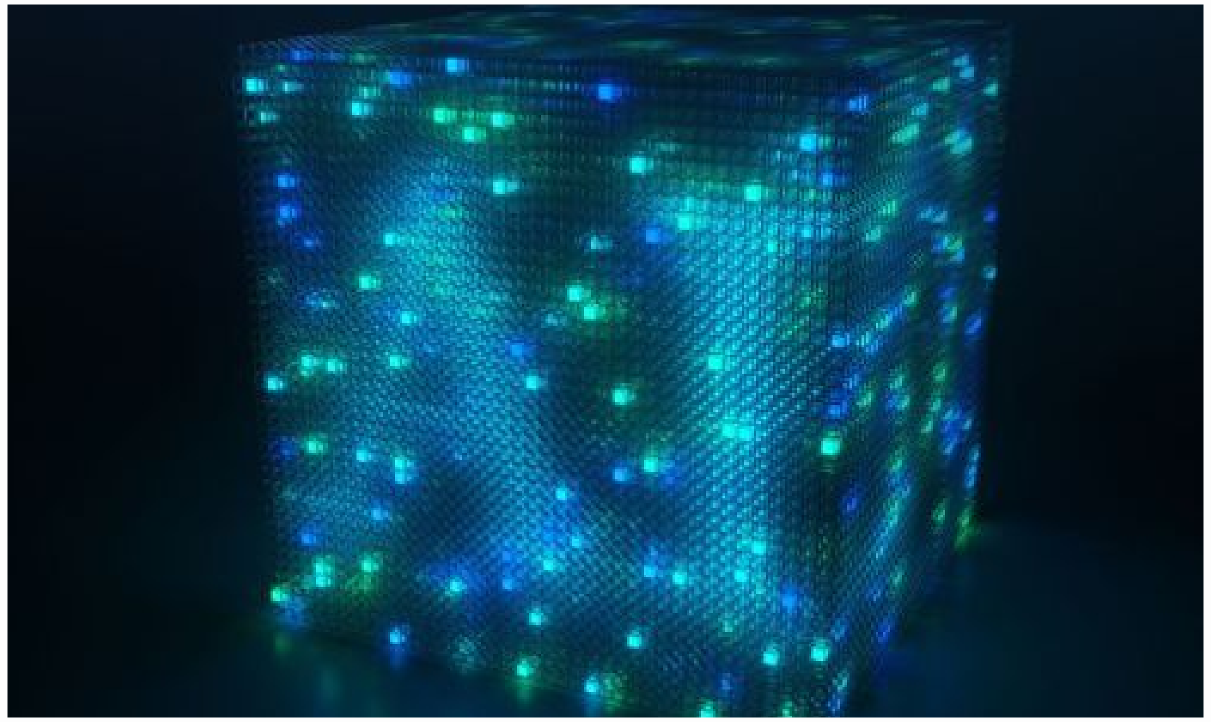


02

- Facilitating data sharing to support AI/ML research and technology development.
- Establishing AI-ready data standards to streamline curation and modeling efforts.
- Creating standardized datasets for consistency and validation.

EMPLOYING EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI)

01 Many ML models act as “black boxes,” making their predictions hard to interpret. In weather forecasting, this lack of transparency challenges result analysis, reliability assessment, and scientific discovery.

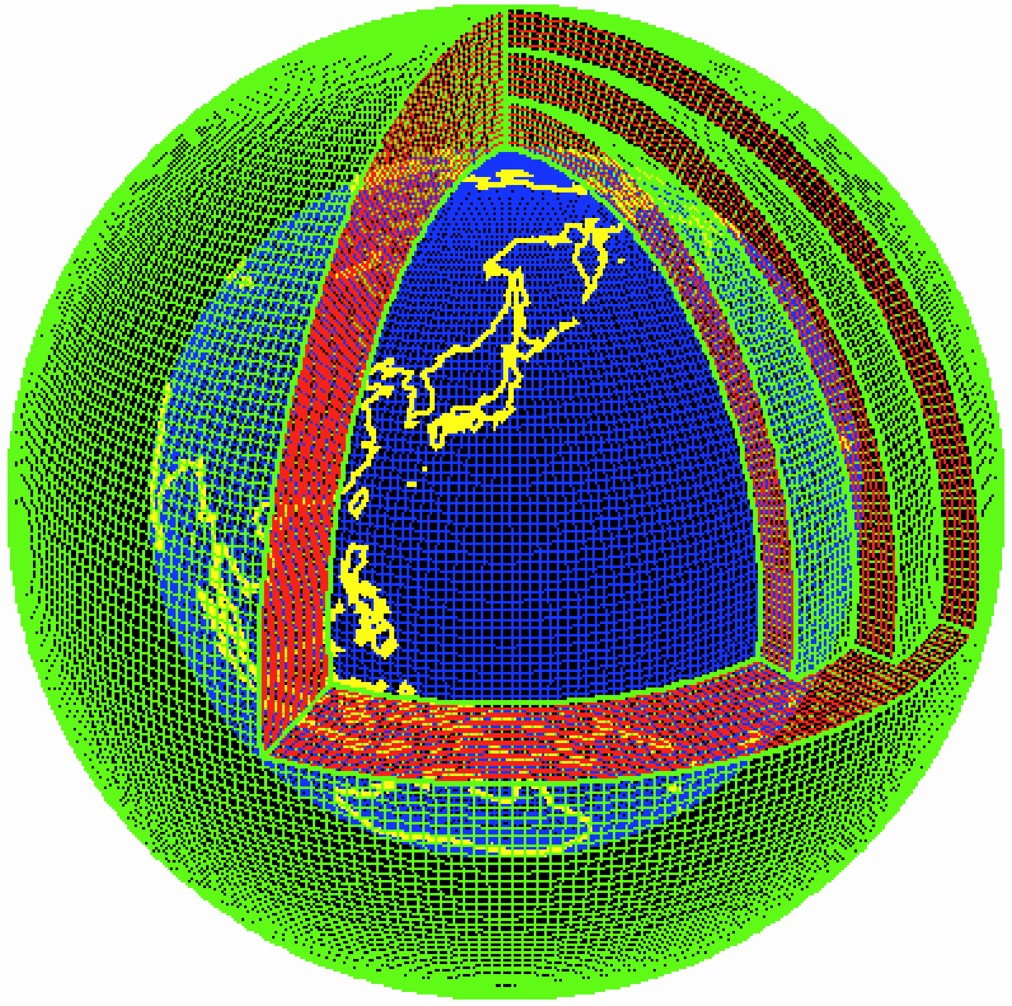


02 **XAI techniques:**

- Surrogates, occlusion analysis, gradients, and relevance propagation for AI explainability.
- PINNs enforcing scientific consistency in ML models.
- Boosting transparency to build user trust.

REAL-WORLD ISSUES

Due to uncoordinated efforts and funding, there's a big gap between ML research and real-world use in the National Weather Service (NWS). Without a clear research-to-operations pipeline, many promising projects never reach implementation.



A structured pathway from exploration to operations is key for ML success:

- Secure sustainable funding for themed projects.
- Engage NWS early to retain expertise.
- Form a consulting team to bridge academia and operations, reducing silos

TECHNICAL SOLUTION

Core Research Problem:

Weather forecasting using Machine Learning (ML) faces major challenges due to inconsistent datasets, lack of domain-specific AI models, and overfitting to historical patterns. Without standardized data and explainable AI techniques, ML models may struggle with accuracy, reliability, and real-world implementation.

- Standardized Datasets for ML Training & Validation
- Explainable AI (XAI) for Trustworthy Forecasting
- Research-to-Operations Pipeline for Real-World Deployment

WHAT TO DO

Phase 3: Narrowing the Topic & Proposed Plan (Mar 18 - Apr 1)

- Define key challenges and technical difficulties.
- Justify problem complexity with specific technical statements.
- Finalize ML techniques for addressing forecasting challenges.

Phase 4: Implementation & Evaluation (Apr 1 - Apr 22)

- Develop and train ML models using selected datasets.
- Optimize model performance and compare with NWP baselines.
- Conduct theoretical analysis and refine techniques.

Phase 5: Final Report & Code Submission (Apr 22 - May 8)

- Complete evaluation and finalize findings.
- Prepare final report with detailed results.
- Submit fully documented and runnable source code.