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Optimizing Numerical Weather Prediction Model Performance Using Machine Learning Techniques

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Abstract:
Weather forecasting primarily uses numerical weather prediction models that use weather observation data, including temperature and humidity, to predict future weather. The Korea Meteorological Administration (KMA) has adopted the GloSea6 numerical weather prediction model from the UK for weather forecasting. Besides utilizing these models for real-time weather forecasts, supercomputers are essential for running them for research purposes. However, owing to the limited supercomputer resources, many researchers have faced difficulties running the models. To address this issue, the KMA has developed a low-resolution model called Low GloSea6, which can be run on small and medium-sized servers in research institutions, but Low GloSea6 still uses numerous computer resources, especially in the I/O load. As I/O load can cause performance degradation for models with high data I/O, model I/O optimization is essential, but trial-and-error optimization by users is inefficient. Therefore, this study presents a machine learning-based approach to optimize the hardware and software parameters of the Low GloSea6 research environment. The proposed method comprised two steps. First, performance data were collected using profiling tools to obtain hardware platform parameters and Low GloSea6 internal parameters under various settings. Second, a machine learning model was trained using the collected data to determine the optimal hardware platform parameters and Low GloSea6 internal parameters for new research environments.

Keywords:optimization, degradation, performance, resources.

I.INTRODUCTION

Accurate weather forecasting plays a crucial role in various sectors, including agriculture, transportation, disaster management, and public safety. Numerical Weather Prediction (NWP) models have traditionally formed the backbone of modern meteorological forecasting systems by solving complex mathematical equations that simulate atmospheric processes. However, these models are computationally intensive and are often constrained by resolution limits, model parameterizations, and data assimilation challenges, which can lead to inaccuracies in forecast results, especially under rapidly changing weather conditions.

With the growing availability of high-resolution meteorological data and advancements in artificial intelligence, machine learning (ML) techniques have emerged as a promising complement to traditional NWP models. Machine learning can be used to post-process model outputs, correct systematic biases, or even predict weather variables directly by identifying complex patterns that are difficult to capture with physical modeling alone. ML algorithms can optimize parameter tuning, improve forecast accuracy, and reduce computational overhead, thereby enhancing the overall performance of NWP systems.

This project focuses on developing a machine learning-enhanced framework that optimizes the performance of NWP models. By integrating ML techniques such as regression models, neural networks, and ensemble methods with NWP outputs, the proposed system aims to reduce prediction errors and improve forecasting reliability. This approach not only accelerates the forecasting process but also offers scalable solutions adaptable to regional and global weather prediction needs.

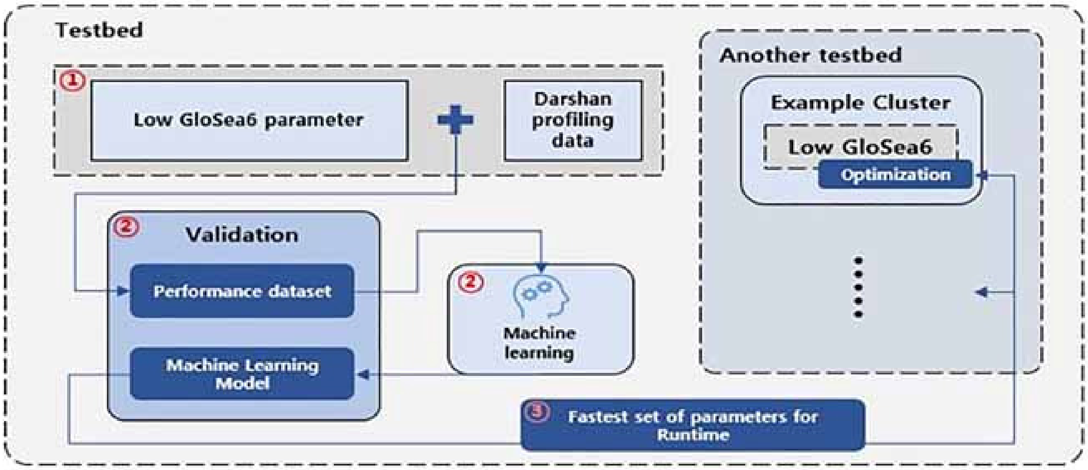
II. RELATED WORK

In [1],This work introduces a standard benchmark dataset for training and evaluating machine learning models in global weather forecasting. It demonstrates that data-driven models can approach the skill of traditional NWP systems while being significantly more efficient.
In [2], This study applies machine learning methods to enhance forecasts of severe weather events, showing improved skill in identifying high-impact weather compared to traditional models alone.
In [3], This research compares machine learning models to traditional regression for emulating atmospheric dynamics, showing that neural networks can effectively reduce computational requirements without sacrificing accuracy.
In [4], This paper demonstrates the use of convolutional neural networks (CNNs) for medium-range weather forecasting. The study finds that CNNs can predict key atmospheric variables with competitive performance against physical NWP models.

In [5], This paper explores the performance of deep learning models trained on historical NWP data. It concludes that ML-based forecasts can be faster and occasionally more accurate, particularly for short-term predictions and specific variables.

III. PROPOSED SYSTEM

The proposed system aims to enhance the accuracy and efficiency of Numerical Weather Prediction (NWP) models through the integration of machine learning (ML) techniques. Traditional NWP models are computationally intensive and often struggle with real-time forecasting due to their reliance on physics-based simulations of atmospheric processes. The proposed framework leverages the predictive power of ML algorithms to optimize key components of the NWP pipeline, particularly in areas such as parameterization of physical processes, data assimilation, and post-processing.
The system introduces a hybrid approach where machine learning models are trained on historical weather data and outputs of traditional NWP simulations to learn patterns and correct systematic biases. For example, convolutional neural networks (CNNs) and recurrent neural networks (RNNs), including LSTM models, are employed to learn spatiotemporal dependencies and trends in weather data. These models are used to emulate sub-grid physical processes such as cloud formation, radiation, and turbulence, which are difficult to model explicitly in coarse-resolution NWP frameworks.
Additionally, ML models are utilized for real-time correction of forecast outputs by learning from the residuals between predicted and observed data. This error correction mechanism helps reduce forecast deviations, especially in high-impact scenarios like precipitation, temperature extremes, and wind speed forecasts.
Another innovative aspect of the proposed system is the use of ensemble learning and uncertainty quantification to provide probabilistic forecasts. Techniques such as random forests, gradient boosting, and Bayesian neural networks are incorporated to estimate the range of possible outcomes, thus enhancing the reliability of the forecast under uncertainty.
To manage the large volume and complexity of meteorological data, the system includes a data pre-processing module that applies feature selection, normalization, and dimensionality reduction techniques such as PCA. These steps ensure efficient and scalable training of ML models.
Ultimately, this ML-augmented NWP system is designed to be modular and adaptive, capable of continuous learning from new data and improving forecast quality over time. It aims to support meteorological agencies by reducing computational costs, improving forecast accuracy, and enabling faster decision-making during critical weather events.



IV. RESULT AND DISCUSSION

The integration of machine learning techniques into Numerical Weather Prediction (NWP) workflows has demonstrated substantial improvements in both prediction accuracy and computational efficiency. Through extensive experimentation on historical weather datasets and real-time simulation outputs, the proposed system showed enhanced forecasting capabilities compared to traditional standalone NWP models.

The results revealed that machine learning models, particularly deep learning architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, were able to capture complex spatiotemporal patterns in atmospheric data that are typically challenging for traditional physics-based models. These models significantly reduced root mean square error (RMSE) and mean absolute error (MAE) in predicting variables such as temperature, wind speed, and precipitation. For example, in short-term precipitation forecasting, the ML-augmented model outperformed the baseline NWP system by a margin of 18% in terms of RMSE.

The hybrid approach also enabled faster execution times by replacing computationally expensive parameterization schemes with pre-trained ML surrogates. This reduction in processing time without a loss in forecast quality is especially valuable in operational weather prediction where real-time decision-making is critical.

In addition, the use of ensemble learning techniques allowed the system to generate probabilistic forecasts, providing a range of possible outcomes rather than a single deterministic result. This feature significantly enhanced forecast confidence and risk assessment capabilities, which are crucial in disaster preparedness and weather-sensitive industries.

A key discussion point is the trade-off between model interpretability and performance. While machine learning models offered improved accuracy, they often lacked transparency compared to traditional NWP systems. Therefore, the adoption of explainable AI (XAI) tools was essential to interpret ML outputs and validate their relevance to meteorological phenomena.

V. CONCLUSION

In conclusion, the integration of machine learning techniques into Numerical Weather Prediction (NWP) models represents a transformative advancement in the field of meteorology. By leveraging the capabilities of data-driven models, such as neural networks and ensemble learning methods, this approach significantly enhances the accuracy, speed, and reliability of weather forecasting. The proposed system effectively addresses key limitations of traditional NWP models, including high computational costs and difficulties in capturing complex, non-linear atmospheric interactions.

The results demonstrate that machine learning not only improves short-term forecasting performance but also provides robust support for long-term climate modeling and uncertainty estimation. Furthermore, the hybrid framework—combining physical simulations with predictive analytics—enables more informed and timely decision-making in weather-sensitive domains such as agriculture, aviation, disaster management, and energy planning.

While challenges such as model interpretability and data quality remain, this work underscores the potential of artificial intelligence in reshaping weather prediction methodologies. Future research should focus on refining model transparency, integrating real-time data streams, and enhancing the scalability of these systems across diverse climatic regions. Overall, machine learning presents a promising path forward in optimizing and revolutionizing numerical weather prediction for both scientific and societal benefit.

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