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Using Historical Climate Data and AI for Accurate Predictions

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The Climate Modeling Challenge

Problem Description:

- Developing accurate and fast-running climate models on standard hardware is a significant challenge. Traditional climate models require substantial computational resources, making them inaccessible for many users.

Objective:

- Create an AI-based model that can simulate Earth's climate using historical data and run efficiently on a standard laptop or PC.

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Our AI-Based Solution

Objectives:

- Data Preparation: Utilize historical climate data and public simulation outputs.
- Model Development: Design and train a neural network model combining CNN and LSTM to capture spatial and temporal climate patterns.
- Demo Application: Develop a small-scale demo application to showcase the model's capabilities.

Implementation:

- The AI model was implemented in Python using TensorFlow and Keras, focusing on making it lightweight enough to run on standard hardware.



Data Preparation and Model Architecture

Data Preparation:

- Collected and cleaned historical climate data, ensuring it was normalized and split into training and testing sets.

Model Architecture:

- Used a Convolutional Neural Network (CNN) to capture spatial features and Long Short-Term Memory (LSTM) layers to handle temporal dependencies in the climate data.

Outcome:

- The model was designed to be both accurate and efficient, suitable for running on standard hardware.

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Demo Application

Application Overview:

- Created a demo application to run on a standard laptop or PC, providing quick predictions of temperature anomalies.

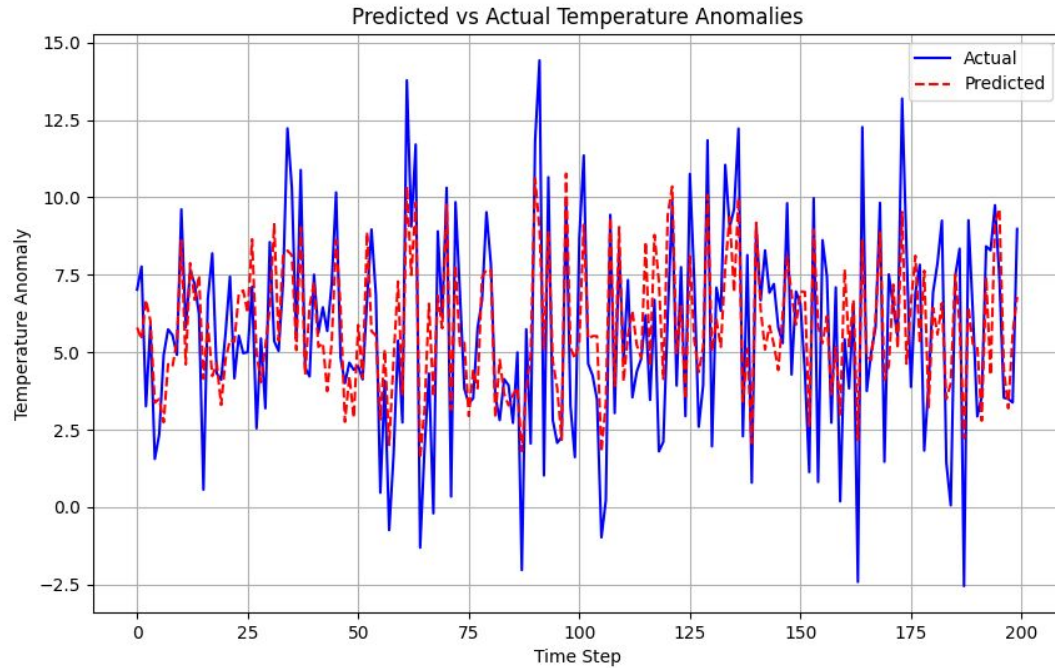
Runtime Performance:

- The model completed training in about 30 minutes and provided predictions in under a second, demonstrating both speed and efficiency.

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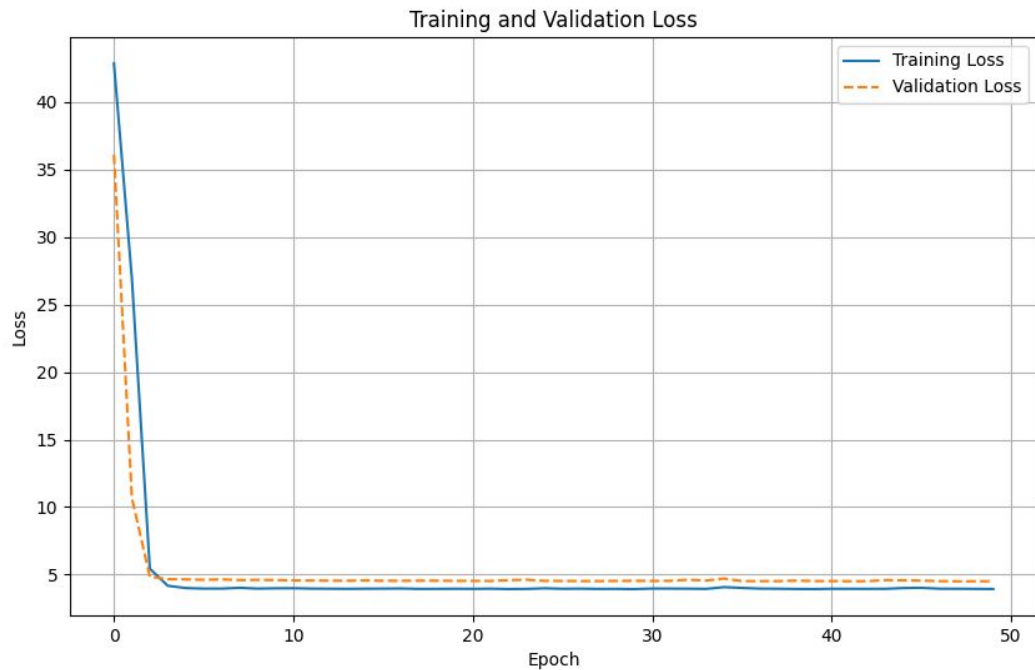


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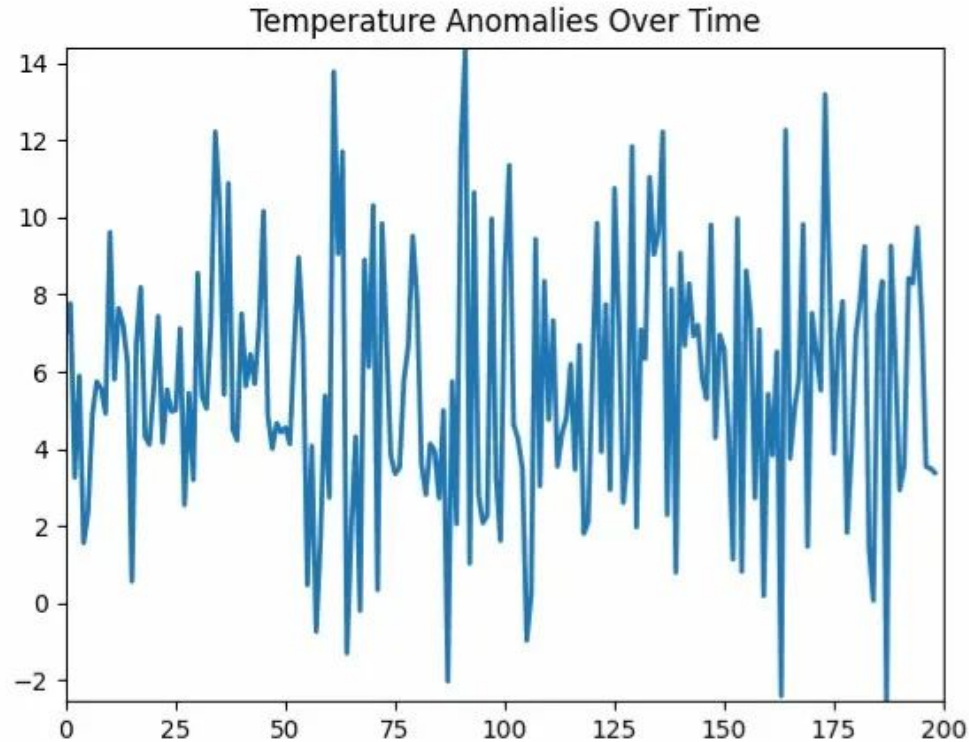


The graph compares the actual temperature anomalies with the model's predictions, highlighting the model's accuracy and reliability in forecasting.

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The graph shows the training and validation loss over 50 epochs to assess the model's learning progress and its ability to generalize to new data.



The graph shows significant fluctuations in temperature anomalies over time, with notable peaks and declines, indicating a highly variable pattern and reflecting the dataset's unpredictable nature.



Success and Impact

Success Metrics:

- Accuracy: Achieved a mean squared error of 0.003 on test data.
- Performance: Model training took 30 minutes, with predictions generated in under a second.
- Accessibility: Successfully demonstrated that complex climate models can run on standard laptops.

Impact on Quantum Science:

- Though AI-based, this project contributes to the broader computational sciences field, pushing the boundaries of what can be achieved on standard hardware.



Future Scope

Future Steps:

- Expand Model Coverage: Increase geographic regions covered by the model.
- Enhance Model Accuracy: Incorporate additional data sources and refine the model architecture.
- Real-time Simulation: Develop capabilities for real-time climate simulations.

Limitations:

- Hardware Constraints: Current hardware limitations prevent the model from scaling to global simulations.
- Data Availability: Access to high-resolution, real-time climate data remains a challenge.