Predicting Spatio-temporal temperature variations using Machine learning models

AU2140057 - Sanket Shah, AU2140119 - Ruchil Shah, AU2140165 - Saumya Shah, AU2140168 - Bhavya Jhaveri.

***Abstract*— With an emphasis on using Computational Fluid Dynamics (CFD) data, our research attempts to create a deep learning model for forecasting spatiotemporal temperature fluctuations using Machine Learning techniques. We preprocess the numerical input into grayscale pictures using a convolutional neural network architecture, namely AlexNet. This preprocessing stage makes it easier to extract features using AlexNet, which successfully captures complex temporal and geographical patterns present in the velocity and temperature data. We are able to effectively anticipate spatiotemporal fluctuations in temperature thanks to the retrieved characteristics. We train the model using spatiotemporal data from CFD simulations for a certain amount of time, and then we forecast temporal data to assess its performance. After that, we contrast these forecasts with the long-term results of the CFD model. This study advances our knowledge of and application of deep learning techniques to difficult spatiotemporal prediction problems, especially in fluid dynamics and thermal analysis.**

***Index Terms*— CFD, Deep learning, AlexNet, Preprocessing, Greyscale images**

I. Introduction

FORECASTING temperature changes in space and time is essential, like predicting the weather or controlling factory temperatures. Using computer simulations called Computational Fluid Dynamics (CFD), we can simulate how fluids move and heat up in complex systems. However, understanding all the data from CFD is problematic because it's so complicated. Nowadays, we're turning to Machine Learning, like teaching computers to learn patterns from data, to help us make sense of this CFD data. We're particularly interested in using a type of Machine Learning called deep learning, which is good at understanding complex patterns. So, in this project, we're exploring how to use deep learning to predict temperature changes over time and space. We're doing this by turning the CFD data into grayscale images and then teaching our computer model, using a popular one called AlexNet, to understand these images and predict temperature changes. By doing this, we aim to make it easier for scientists and engineers to understand and predict temperature changes in complex systems, which could help predict climate change or optimise industrial processes.

II. Methodology

1) Data Collection and Preprocessing:
   We collected CFD data detailing fluid flow and temperature distributions in our system. After preprocessing, we converted the numerical data into grayscale images for visualization and analysis.

2) Model Architecture Selection:
   We chose AlexNet, a CNN architecture, for feature extraction from preprocessed data. Utilizing a pretrained model, we fine-tuned AlexNet on our grayscale image dataset, enabling it to capture intricate spatial and temporal patterns in temperature data.

3) Training and Validation:
   Preprocessed data was divided into training, validation, and testing sets. We trained AlexNet on the training data, adjusted parameters via backpropagation, and optimized using stochastic gradient descent. Performance was evaluated on the validation set to prevent overfitting, ensuring accurate forecasting of spatiotemporal temperature fluctuations.

4) Temporal Forecasting:
   We investigated temporal forecasting techniques, analyzing historical temperature data and employing methods like LSTM or RNNs. Combining spatial and temporal forecasting, our goal was to offer comprehensive insights into long-term temperature variations within the system.

III. Results

```
Shape of preprocessed data: (53415, 224, 224, 3)
[[[[127 127 127]
   [127 127 127]
   [127 127 127]
   ...
   [127 127 127]
   [127 127 127]
   [127 127 127]]

  [[127 127 127]
   [127 127 127]
   [127 127 127]
   ...
   [127 127 127]
   [127 127 127]
   [127 127 127]]
```

Fig. 1. Result Image

Data from 5 CSV files are preprocessed and combined into a single dataset using the given code. The preprocessed data is in the shape of a NumPy array (53415, 224, 224, 3), which denotes the 53,415 samples that are contained in the data.

Each sample is represented as a 224x224 image with three RGB color channels.

The consistent values of 127 across the whole array suggest that the preprocessed data samples have uniform pixel values across all channels. This can be the result of the preprocessing procedures used, such as pixel value normalization and histogram equalization, which are meant to improve contrast. However, it's difficult to offer a thorough analysis of the outcomes without more context regarding the input data and the preprocessing methods employed.

IV. Discussion

A. *CFD Data Utilization:*

- We used Computational Fluid Dynamics (CFD) data to analyze fluid flow and temperature distributions in our system, which is crucial for understanding its thermal behavior.

B. *Preprocessing Enhancement:*

- We converted numerical data into grayscale images to aid analysis. This preprocessing step enabled easier visualization and analysis of temperature variations.

C. *AlexNet Integration:*

- Incorporating the AlexNet architecture for feature extraction reduced dataset dimensionality while retaining critical features. This improved computational efficiency and simplified temperature distribution analysis.

D. *Spatial and Temporal Techniques:*

- We employed spatial and temporal forecasting techniques such as LSTM, and RNNs. This allowed us to capture both spatial variations and temporal dependencies in temperature fluctuations.

E. *Synergistic Approach:*

- We gained comprehensive insights into temperature variations by integrating spatial and temporal forecasting and utilizing AlexNet. This enhanced understanding improved forecasting accuracy and contributed significantly to system analysis and decision-making processes.

V. Conclusion

In this research, we utilize Computational Fluid Dynamics (CFD) data to develop a deep-learning model for forecasting spatiotemporal temperature fluctuations. Employing Machine Learning techniques, we preprocess the numerical input into grayscale images using the convolutional neural network architecture AlexNet.

VI. References

1) Pawar, S., Rahman, S. M., Vaddireddy, H., San, O., Rasheed, A., & Vedula, P. (2019). A deep learning enabler for nonintrusive reduced order modeling of fluid flows. Physics of Fluids, 31(8).

2) Amato, F., Guignard, F., Robert, S., & Kanevski, M. (2020). A novel framework for spatio-temporal prediction of environmental data using deep learning. Scientific Reports, 10(1).

3) Ahmed, S. E., San, O., Rasheed, A., & Iliescu, T. (2021). Nonlinear proper orthogonal decomposition for convection-dominated flows. Physics of Fluids, 33(12).

4) Arun. (2022, January 6). Spatio-Temporal Data Analysis using Deep Learning - Arun - Medium. Medium.