APPLICATION OF MACHINE LEARNING IN PREDICTING GASEOUS PROPERTIES OF EARTH ATMOSPHERE

Midway Presentation

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INTRODUCTION

- Radiative Transfer Models (RTMs) are used to study how energy from the sun is absorbed, reflected, and scattered by the Earth's atmosphere.
- RTE+RRTMGP is a RTM used to simulate this energy transfer.
- RRTMGP uses precomputed lookup tables (LUTs) to speed up calculations. However, LUTs have limitations, especially in terms of speed and accuracy.
- The main goal of the experiment is to emulate the RRTMGP look-up tables using neural networks and investigate the advantages of this utilization.

MOTIVATION

- LUTs have some setbacks
- LUTs require large storage space to store pre-calculated radiative transfer solutions for different atmospheric conditions.
- They are computationally expensive when a wide range of atmospheric conditions and input parameters are required.
- Accurate only within the pre-calculated range of atmosphere.
- Literature review suggests that neural networks can speed up calculations and improve data interpolation for a range of atmospheric conditions.

RELATED WORKS

Topic	Year	ML models used
Predicting atmospheric optical properties for radiative transfer computations using neural network (Menno A. Veerman et al)	2021	Feedforward Neural Network (FNN)
Accelerating Radiation Computations for Dynamical Models With Targeted Machine Learning and Code Optimization (Peter Ukkonen et al)	2020	Feedforward Neural Network (FNN)
Exploring Pathways to More Accurate Machine Learning Emulation of Atmospheric Radiative Transfer (Peter Ukkonen)	2022	FNN and Recurrent Neural Network (RNN)
RadNet 1.0: exploring deep learning architectures for longwave radiative transfer (Liu, Ying ; Caballero, Rodrigo; Merwin Monteiro, Joy)	2021	FNN and Convoluted Neural Network (CNN)

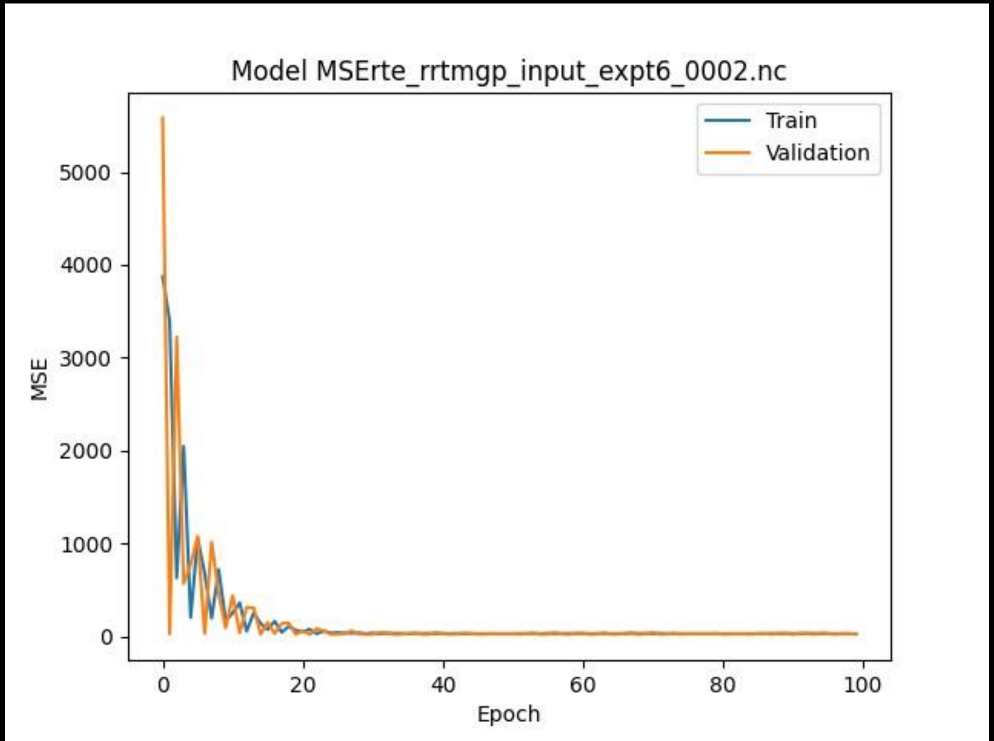
GOALS

- Using neural networks to emulate the RRTMGP look-up tables.
- Verify its advantages over LUTs.
- Discuss the potential impact of using neural networks for atmospheric modeling and climate research.
- Explore ML-based optimization possibilities.

MIDWAY PERFORMANCE

- Reviewed related papers and looked up the required codes.
- Studied tensorflow, docker, build automation.
- Generated 3600 atmospheric profiles which have some degree of realism.
- Developed a feed-forward neural network to emulate the look-up tables and trained it using 3600 atmospheric profiles.
- Verified that the feedforward neural network code that was developed is functioning properly.
- The layer temperature was used to predict the water vapor concentration.
- The temperature was the parameter, while the number of epochs and learning rate were the hyperparameters.
- The number of hidden layers and nodes in each layer in the FNN were varied and MSE v/s epoch was plotted.

GRAPHS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Validation
MSE
Epoch
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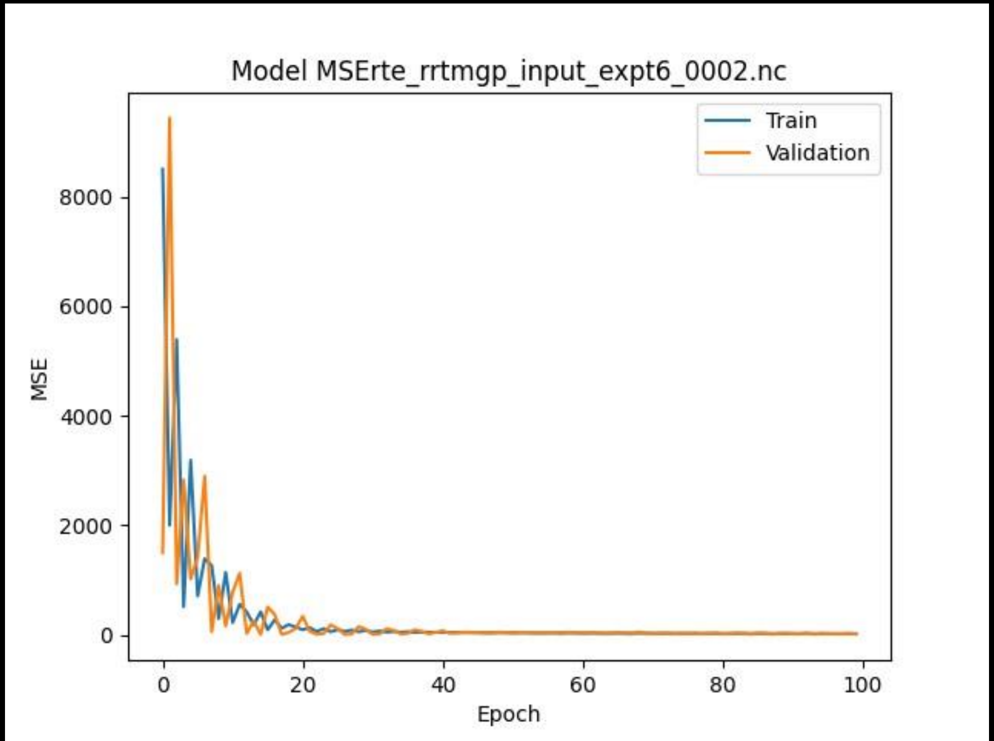
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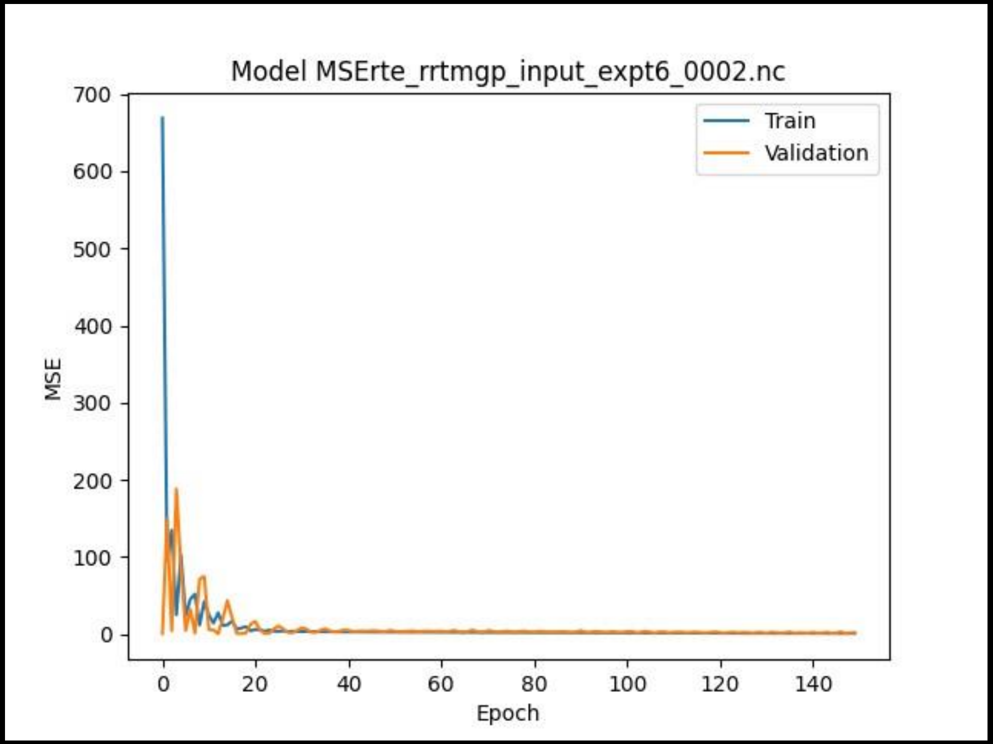

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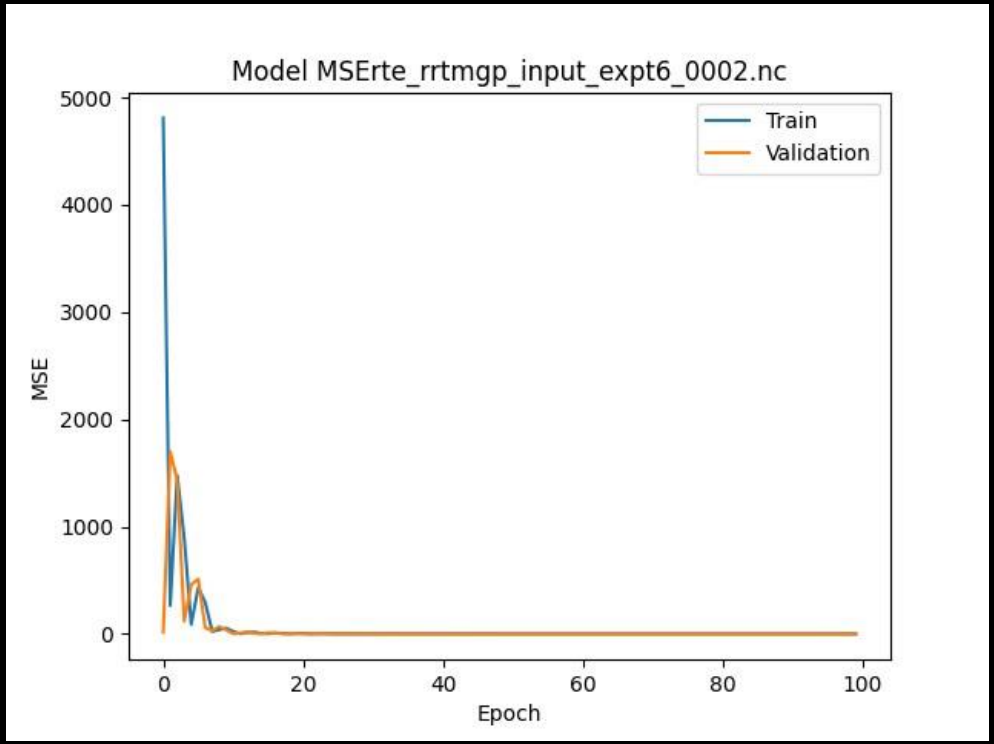

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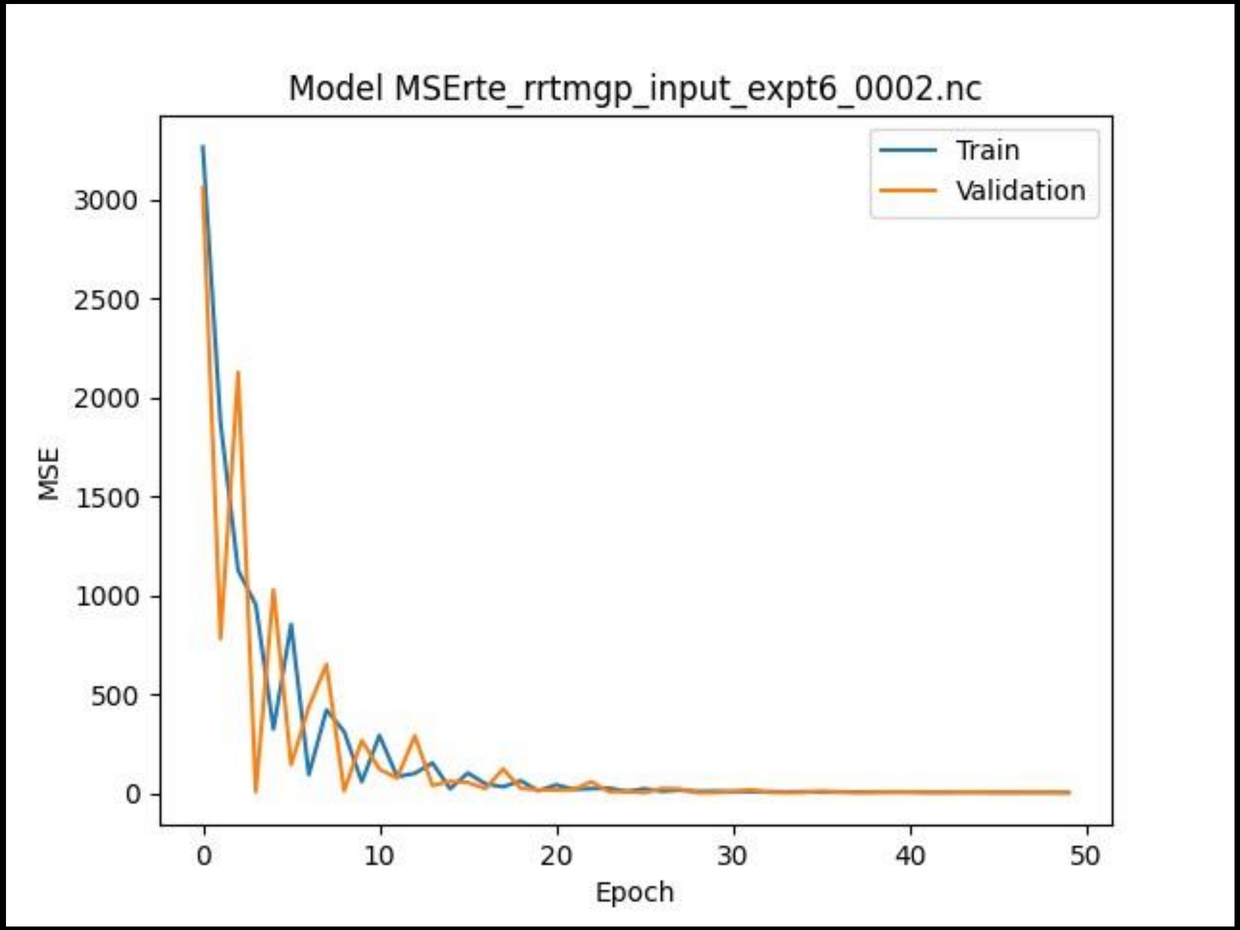
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50
Epoch

FUTURE PLANS

LABELLING	PROFILE GENERATION	RNN	COMPARISON
The datasets will be labelled and trained, validated, and tested on feed forward neural networks	More atmospheric profiles will be generated from different datasets like CAM5, CKDMIP	Training, validating, and testing on Recurrent Neural Networks (RNNs).	The performance of the RNN model will be compared to that of the previous model.