Assignment 3 Project Report

Introduction:

The goal of the project is to create and validate various deep-learning models for climate-based time series forecasting.

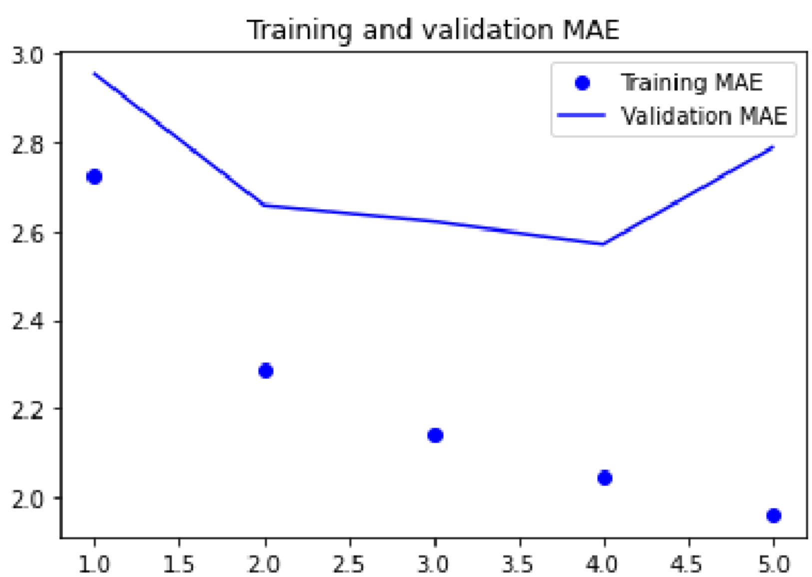
Model Evaluation:

MSE loss function, MAE metric, and rmseprop optimizer were used to understand how different methodologies influence model performance. We have used the MAE metric instead of accuracy because MAE is better than Accuracy for temperature predictions. After all, the purpose of temperature prediction is to predict constant numerical values.

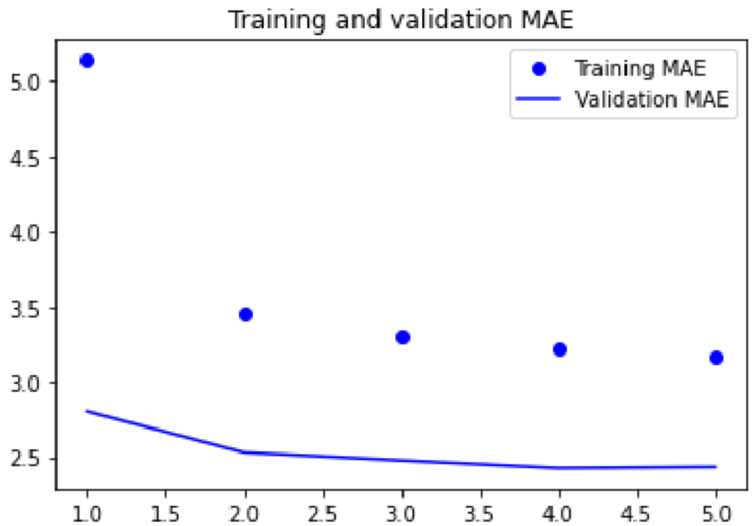
Summary:

- Adding more dense units to the hidden layers does not always result in better performance. Sometimes, models with fewer units do better in terms of accuracy.
- When running the base machine learning model using different dense units (e.g., 16, 32, 64) the 16 and 32 units have the highest Test MEO. We have included the 16 dense units to check the Test MEO and loss function of the 1D convolution model as well as other RNN models (such as the LSTM layer model, GRU model, and bidirectional LSTM model).

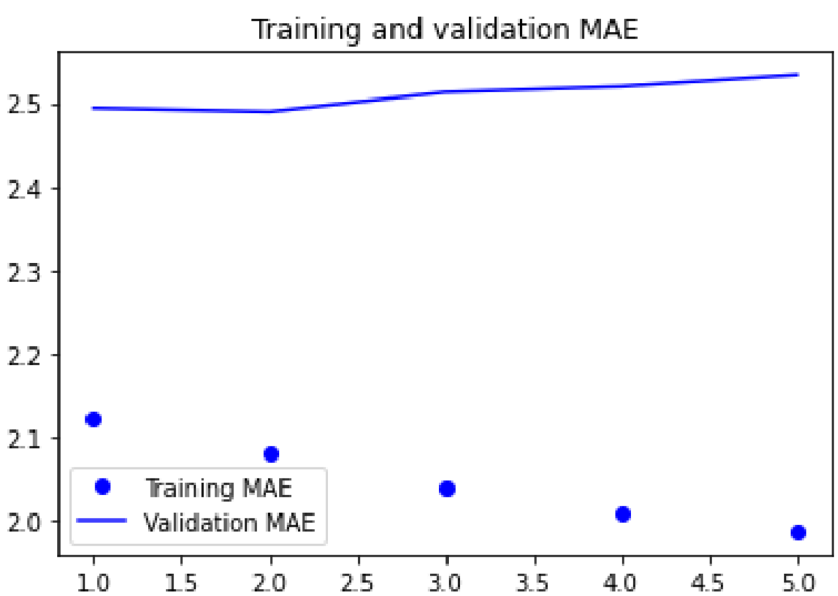
Results:



- The configuration 16 achieves the highest maximum observed error (MAE) of 2.61, with a loss function of 10.9803, but there is little difference between all the combinations.
- Of all the combinations tested except GRU, the LSTM model (0.5 dropout) has the highest MAE (2.61) and the lowest loss function (11.1563).



- Combined LSTM with 0.5 dropout and 1d_conversions because it has the highest minimum observed error (MAE). The combination provides the highest MAE of all models with a minimum observed error (MAE) of 2.71 with loss function (12.1350).



Model	Dense Units	Loss	Test MAE
Simple LSTM	16	10.9803	2.60
Simple LSTM	8	11.6319	2.69
Simple LSTM	32	10.9803	2.61
Simple LSTM	64	11.6319	2.69
1D Convolution model	16	16.2496	3.18
RNN models			
LSTM layers	16	11.2803	2.64
LSTM layers	16	11.1563	2.61
GRU (later replaced with LSTM	16	10.2277	2.50
Bidirectional LSTM model	16	10.4592	2.53
Combination of 1d_Convent and LSTM model with dropout			
Model	16	12.1350	2.72

Conclusion:

This project explored various deep learning models for time series forecasting of climate data. Several architectures were evaluated, including simple dense models, 1D convolutional models, LSTM models with different units and dropout, GRU models, and bidirectional LSTM models. The models were compared using the mean squared error (MSE) loss function and mean absolute error (MAE) metric.

The key findings from this study would be Increasing the number of dense units in the simple models did not necessarily improve performance. Models with 16 and 32 dense units performed better than those with 64 units. Among the recurrent neural network (RNN) models, the LSTM model with 16 units and 0.5 dropout achieved the highest MAE of 2.61 and the lowest loss of 11.1563. Combining the 1D convolutional model with the LSTM model with dropout resulted in the highest overall MAE of 2.72, although it had a slightly higher loss of 12.1350. The GRU model performed well, with an MAE of 2.50, but the LSTM models generally outperformed the GRU model.

Overall, the LSTM models, particularly with dropout regularization, demonstrated promising performance for climate-based time series forecasting tasks. The combination of 1D convolutions and LSTM layers also showed potential for further improvement. Future work could explore more advanced architectures, optimized hyperparameters, and ensemble methods to enhance the forecasting accuracy further.