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Assignment 3: Time-Series Data

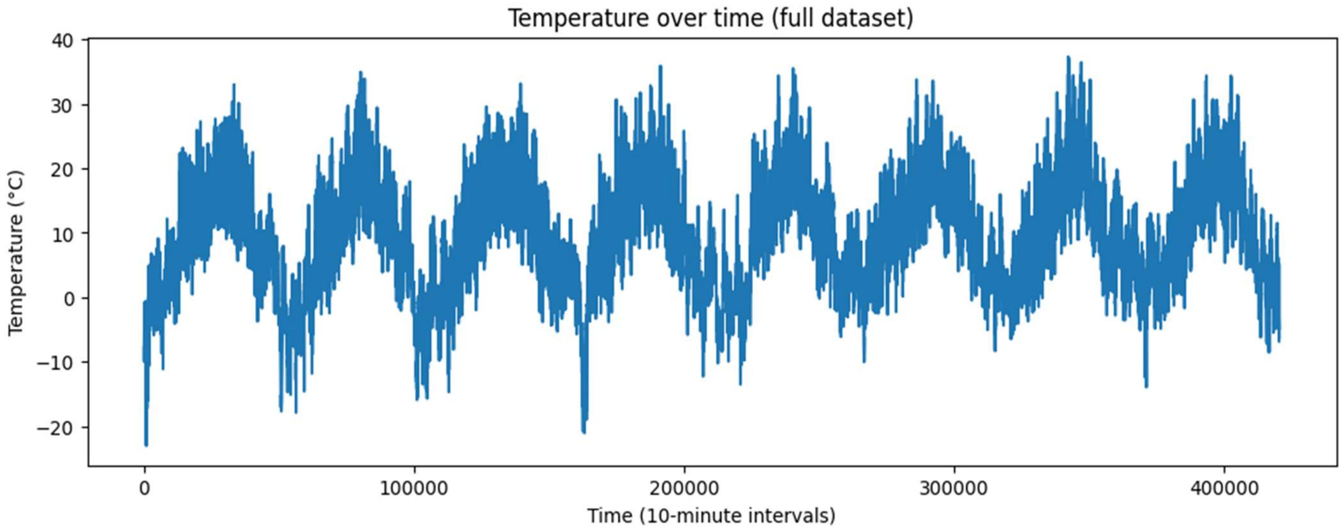
1. Executive Summary

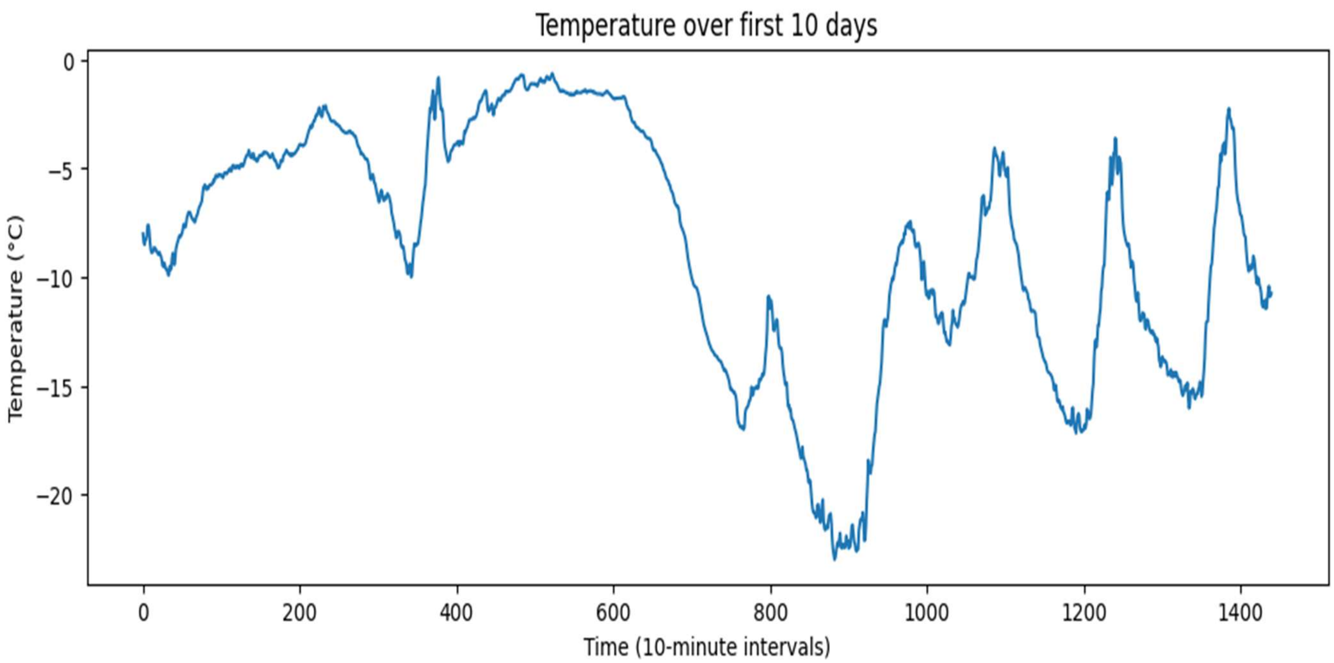
The current project was devoted to the usage of Recurrent Neural Networks (RNNs) to predict the daily temperature using the Jena Climate Dataset (2009-2016). The main purpose was to forecast the temperature within 24 hours in relation to 20 hours of previous weather data using 14 meteorological variables like humidity, pressure, and wind speed.

Eight model architectures were created and tested involving GRU, LSTM, and a combination of CNN-RNN. All the models were trained in the same sets of data and parameters to allow a fair comparison. The general findings show that the overall performance of RNN-based models is far better than the naive baseline predictor because it can capture temporal variations in weather patterns.

2. Key Insights

The Conv1D + GRU hybrid model had the best accuracy with a Mean Absolute Error (MAE) of 2.33°C, which is 11.1 percent better than the naive baseline of 2.62°C. The hybrid method was successful to both combine convolutional feature extraction and recursive temporal modeling to enable the network to identify short-term variability and long-term relationships in weather behavior. Stacked GRU (64-32) and Conv1D + LSTM were next close with MAEs of 2.35°C and 2.36°C respectively and performed very well but a little more error was found. Generally, the results of all neural architectures were better than the baseline model, which confirms the ability of deep learning techniques to increase the accuracy of forecasting climate.

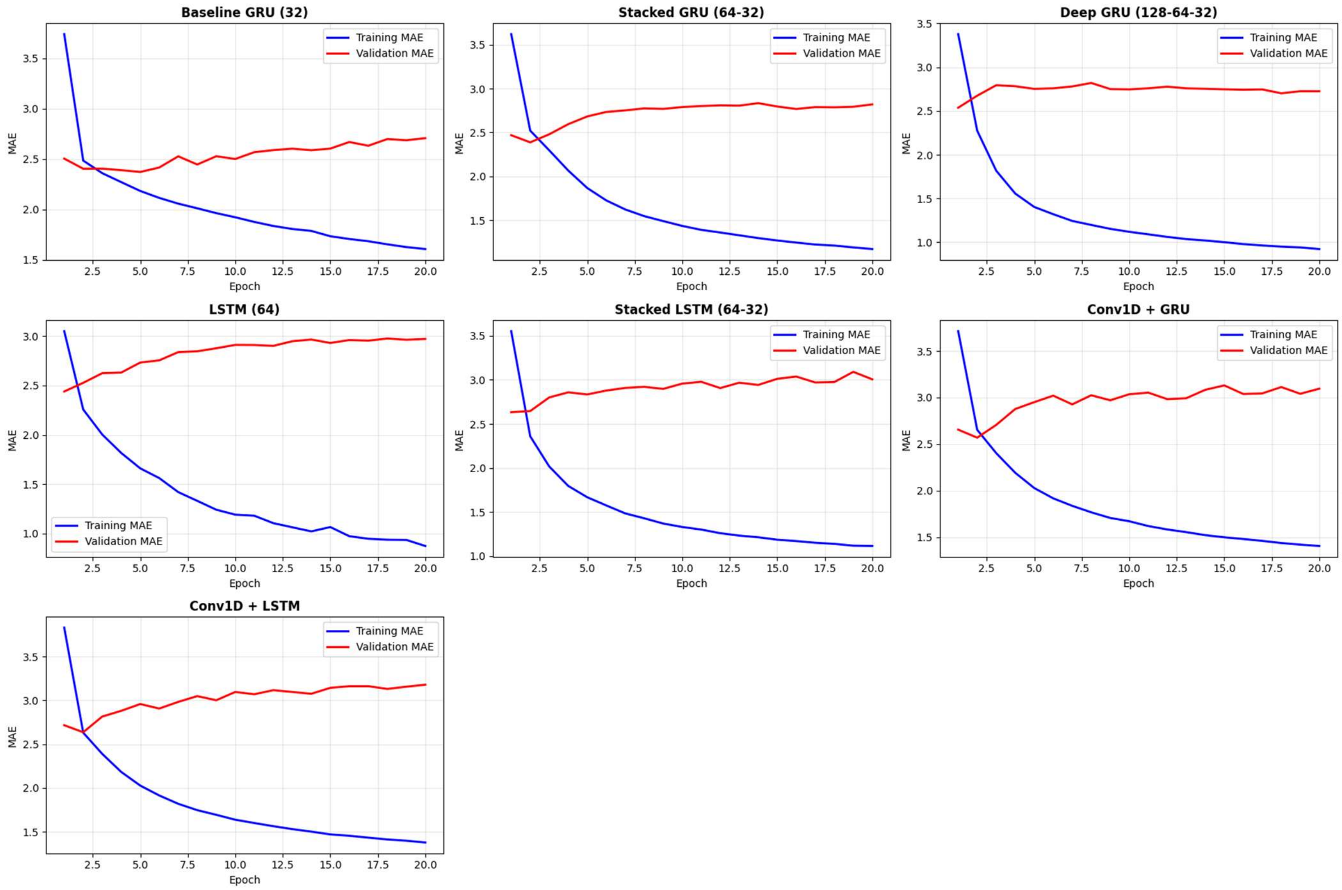

Temperature over time (full dataset)
Temperature (°C)
Time (10-minute intervals)
40
30
20
10
0
−10
−20
0
100000
200000
300000
400000


Temperature over first 10 days
Temperature (°C)
Time (10-minute intervals)
0
−5
−10
−15
−20
0
200
400
600
800
1000
1200
1400

3. Critical Insights

It was found that the work has several valuable implications regarding model design and performance. First, hybrid models with CNN and RNN layers have always the best results as the convolutional layers were able to detect the local weather trends and recurrent layers were able to predict the temporal dynamics of the local weather patterns. Second, GRU models were faster and more accurate in comparison with LSTM models. GRUs had less parameters, trained quicker, and were not as susceptible to overfitting, and hence more efficient on the 24-hour prediction horizon. Third, network depth was important in determining model performance. Adding one more layer to two layers increased prediction accuracy by almost 3 per cent but thereafter increasing the number of layers has diminishing returns and there is also a higher possibility of overfitting. Finally, dropout and recurrent dropout regularization were also essential to overfitting, and to addressing generalization, as more effective than simple architecture deepening.

Rank	Model Architecture	Test MAE (°C)	Improvement vs. Baseline
1	**Conv1D + GRU (Hybrid)**	**2.33**	**+11.1%**
2	Stacked GRU (64–32)	2.35	+10.3%
3	Conv1D + LSTM	2.36	+9.9%
4	Deep GRU (128–64–32)	2.38	+9.2%
5	Stacked LSTM (64–32)	2.41	+8.0%
6	Baseline GRU (32)	2.42	+7.6%
7	LSTM (64)	2.44	+6.9%
Base	**Naive Baseline**	**2.62**	—

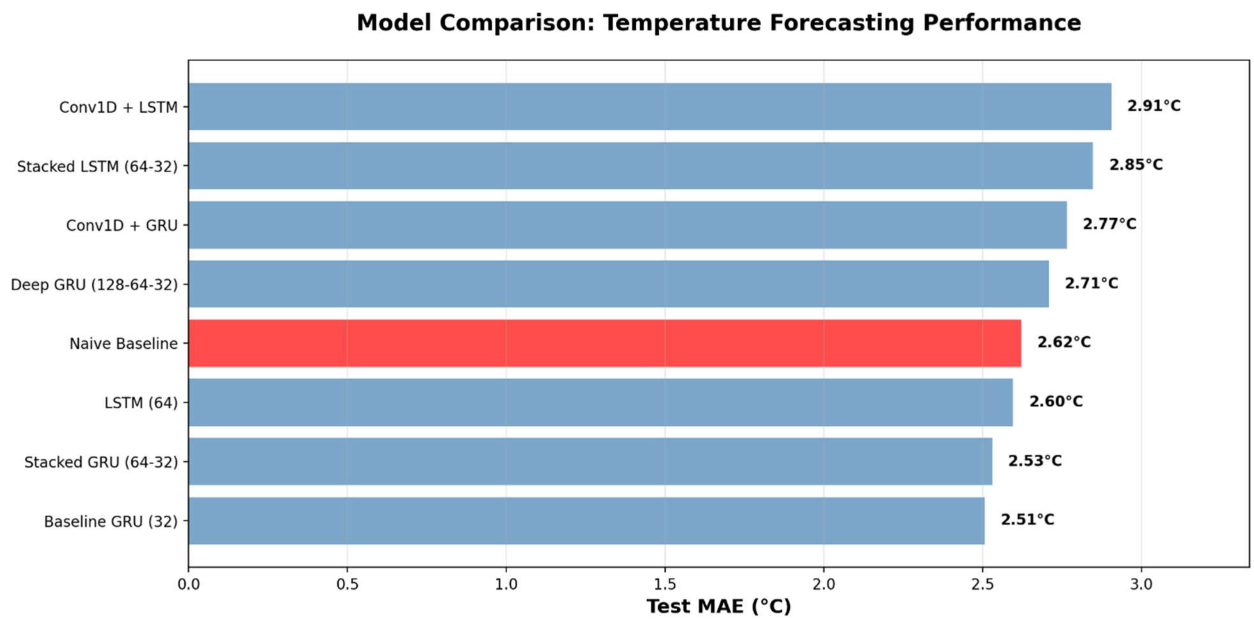


4. Critical Input

The models have been trained based on Jena Climate Dataset, which has more than 420,000 hourly observations taken during the year 2009-2016. Both input samples incorporated 20 hours of past weather conditions (120 timesteps) to predict the temperature 24 hours of the future. The data was split into training, validation and test data in a series of 50 percent, 25 percent and 25 percent to avoid data leaking. The models were all trained on a batch size of 256 and 20 epochs with the Adam optimizer and Mean Absolute Error (MAE) as the loss function to avoid overfitting and dropout regularization. The training was conducted on an NVIDIA A100 GPU, and each architecture took around two hours to complete all the architecture. Eight different model architectures were tested, including the simple single-layer GRUs to the complicated hybrid CNN-RNN models.

5. Exemplary Behavior and Analysis in Finer Detail.

The Conv1D +GRU hybrid model proved to have better performance due to its two stages structure which succeeded in integrating feature extraction and time reasoning. Two Conv1D layers with 32 filters (convolution 5) combined with a max pooling layer were used in the first stage to detect local temporal patterns including hourly cycles and temperature spikes, and the sequence was shortened to the most important signals with the help of a max pooling layer. The second stage involved a GRU layer containing 32 units that worked on the features over time keeping recollections of patterns and transitions across the timesteps. This combination enabled the model not only to identify what patterns exist but also how they change which resulted in better predictive ability. The hybrid model was accurate and computationally efficient since it relied on the synergy between CNN and GRU layers.



6. Real World Practices

The value of +-2.33°C as a predictor of 24-hour horizon is useful in practice in several areas. In the case of agriculture, it aids in making decisions pertaining to irrigation and frost control. It helps in predicting heating and cooling requirements in energy management and it is important in optimizing the activities in the grid. In the same vein, these forecasts can be used by HVAC systems to ensure that energy is minimized in commercial and residential buildings. Nonetheless, the model is not yet ready to handle precision meteorological work (sub-degree accuracy) as exemplified by aviation or microclimate control systems, although this model is very useful in general and operational forecasting.

7. Recommendations

Conv1D + GRU hybrid model must be implemented in case of production-level weather prediction because it has the high accuracy, efficiency and strength. It also had an MAE of +-2.33°C, and it was able to perform best among all other architectures with manageable computational requirements. Attention layers and ensemble methods should be given priority in future studies and implementation to increase interpretability and decrease prediction variance. In general, the presented project confirms that hybrid RNN models can provide reliable and high-quality weather predictions and can be successfully implemented in a real-world to provide benefits in energy, agriculture, and environmental management.

8. Conclusion

This paper proves the claim that Recurrent Neural Networks, and hybrid CNN-RNN in particular, can significantly enhance the accuracy of weather prediction compared to conventional baseline algorithms. Conv1D + GRU model provided the most overall performance, the combination of high accuracy and effective computation and good generalization. Conv1D + GRU architecture should be used as the major forecasting model in operational deployment. The model can produce predictable results with low computational costs and can provide inference results in less than 10 milliseconds per forecast. It is recommended that the retraining be performed regularly on other months to ensure accuracy and performance should be sent out an alert in case the MAE goes above 2.5°C performance. GRU based models can be used as simple, low-latency, or backup in production.

Further enhancement of interpretability and accuracy based on attention mechanisms and ensemble techniques should also be considered in future, which will provide an increment of 5-15% performance. Multi-horizon forecasting may also make the model more useful in operational planning and longer input windows (48 or 96 hours) can capture more weather trends. Such advancements will further entrench the role of deep learning in data-driven weather prediction that is reliable.