ASSIGNMENT – 3

TIME SERIES DATA

Applying RNNs to Time-Series Data for Weather Forecasting

1) INTRODUCTION:-

The primary objective of this study is to forecast weather time series using Recurrent Neural Networks (RNNs). This involves testing different network topologies and configurations in order to improve the model's predicting accuracy, as shown by the Mean Absolute Error (MAE).

1. creating a forecasting RNN model that works well.
2. playing about with GRU and LSTM layers.
3. integrating RNNs with 1D convolutional layers and fine- tuning recurrent layer units to improve performance.

2) DATA PREPARATION:-

Temperature readings are the main emphasis of the weather dataset, which covers several years and a variety of environmental variables. This time-series data must be loaded, visualized, and normalized as part of the first data preparation processes before being entered into RNN models.

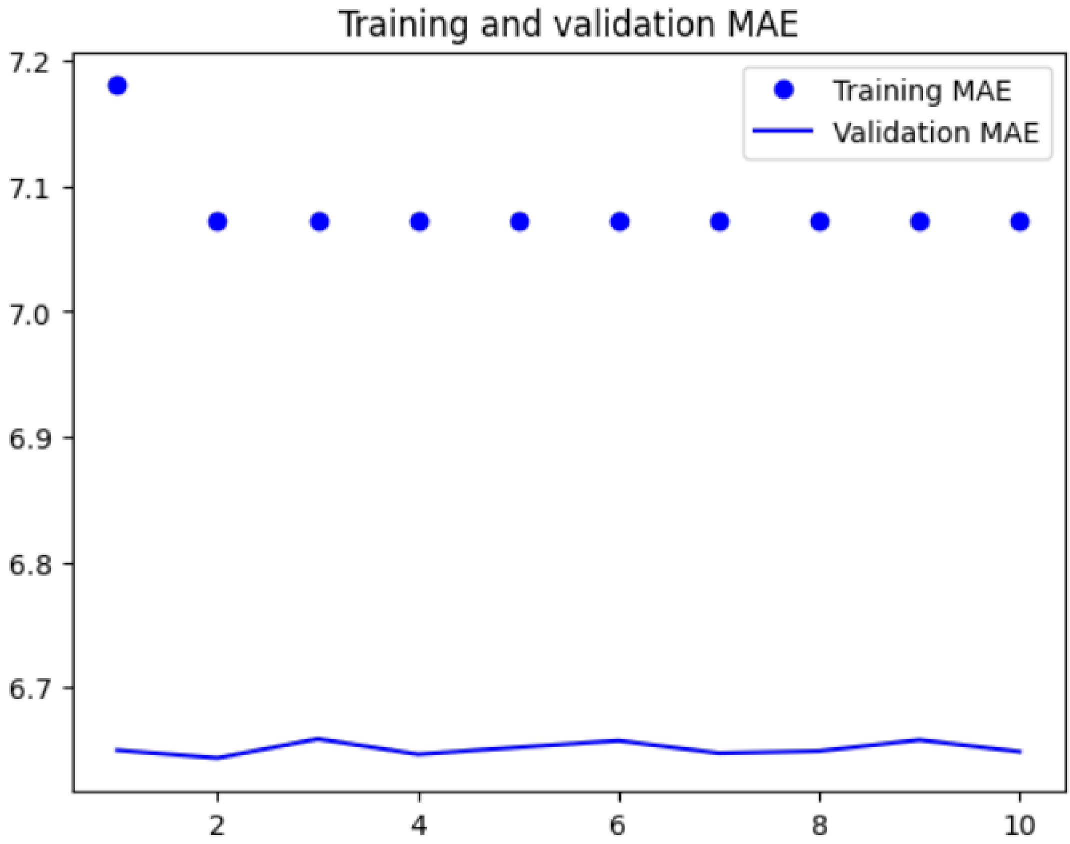
3) MODEL DESIGN:-

There were three main model architectures created

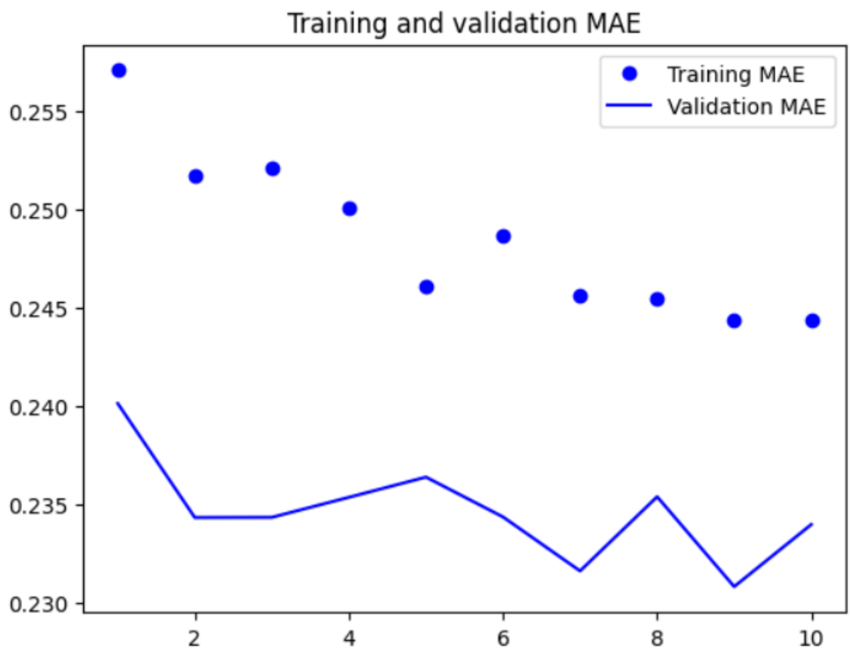
1. The baseline RNN model makes use of a straightforward LSTM/GRU architecture.
2. The improved RNN model uses dropout to avoid overfitting and increases the number of recurrent layer units.
3. To capture local patterns, the Hybrid RNN-Conv1D Model combines RNNs with 1D convolution layers.

4) EXPERIMENTAL DESIGNS:-

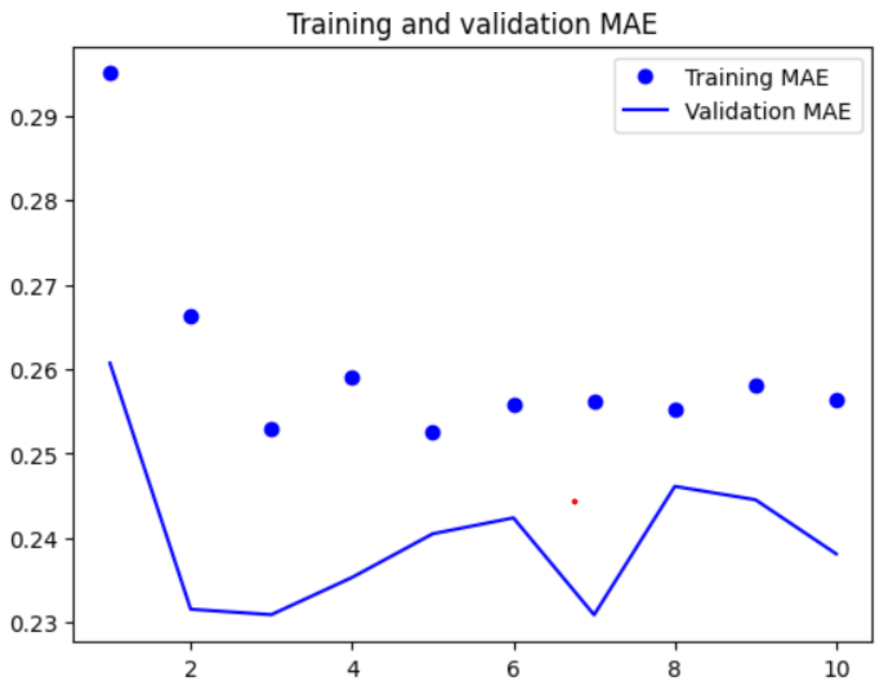
1. Recurrent layer of 32 units



2. LSTM



3. 1d-CNN+LSTM



A summary table of model performance, comparing validation Mean

Model architecture	Units per layer	Training MAE	Validation MAE	Testing MAE
Recurrent layer	32	7.7	6.6	6.64
Recurrent layer	64	0.26	0.25	8.49
LSTM	16	0.23	0.234	0.28
1d-CNN+LSTM	-	0.25	0.23	0.24
Stacked LSTM	32	0.25	0.251	0.23

Absolute Error (MAE) for different architectures and configurations:

CONCLUSION:-

With the lowest testing MAEs (0.24 and 0.23, respectively) and the best generalization, the 1D-CNN + LSTM and Stacked LSTM models performed better than the other designs. These models are perfect for time-series forecasting because they can capture both long-term dependencies and local patterns. The bigger recurrent layers (32 and 64 units) either underperformed or overfitted, indicating the significance of model complexity in reaching accurate predictions, even if the basic LSTM with 16 units also demonstrated consistent performance.