Regional Weather Forecasting Using Neural Networks

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Understanding the Challenge

Overview of 2020 Weather Patterns:

- "Record low precipitation levels and unusually high temperatures observed across key agricultural regions in Canada."
- "Statistics: Specific regions experienced rainfall deficits up to 50% below the long-term average."

Micro-Climate Prediction

Micro-climate predictions focus on localized weather forecasting, crucial for agricultural decisions like planting and irrigation scheduling.

Our Approach

- "Our project uses MLP (Multilayer Perceptron) and TDNN (Time Delay Neural Network) to analyze patterns in temperature, precipitation, air pressure, and sunlight."
- "These models are trained on historical weather data, enabling them to predict future conditions with higher accuracy than traditional methods."

Leveraging MLP and TDNN for Precision Prediction

Introduction to MLP and TDNN:

- MLP (Multilayer Perceptron): "A type of neural network known for its ability to learn and model non-linear and complex relationships. MLPs are composed of at least three layers of nodes: an input layer, a hidden layer, and an output layer."
- TDNN (Time Delay Neural Network): "Specialized for temporal data processing, TDNNs are effective at recognizing patterns across time, making them ideal for sequential prediction tasks like weather forecasting."

Why MLP?:

- Pattern Recognition Capabilities
- Adaptability to Non-linear Relationships

Why TDNN?:

- Handling Temporal Sequences
- Improving Forecast Accuracy

Data

- Data source
  - Canada Weather Stats (WeatherStats.ca)
  - Two stations: Ottawa and Ottawa South

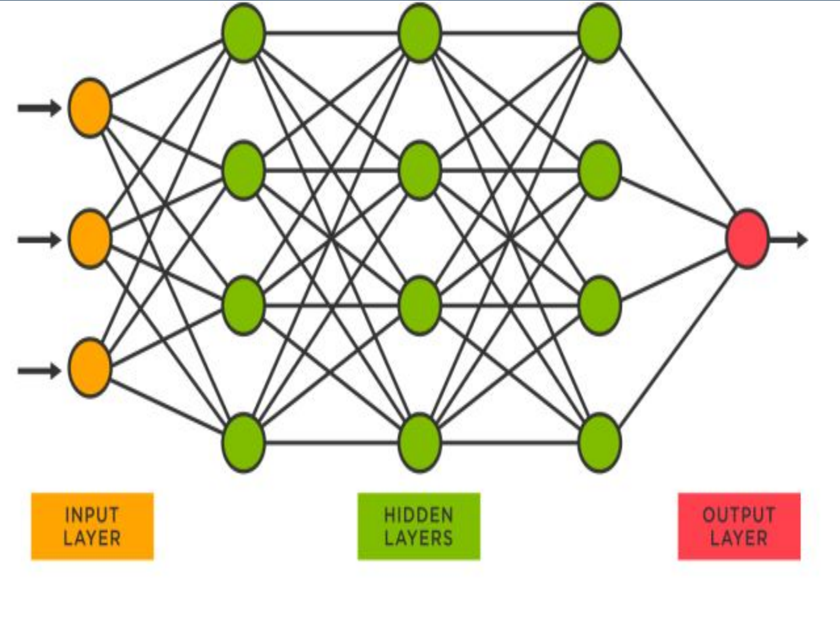
- Data processing
  - Interpolation of Missing Values
  - Feature Selection
  - Normalization: MinMaxScaler
  - Data Transformation

Model Attributes (both models):

- Avg. hourly temperature (℃)
- Precipitation (mm)
- Air pressure at station (psi)
- Solar radiation (kJ/m²)

Model specifics: MLP

- Architecture:
  - Input Layer: processed and scaled weather data
  - Hidden Layers: Two layers with 128 and 64 neurons respectively, using ReLU activation functions to introduce non-linearity.
  - Output Layer: Produces forecasts for weather parameters
- Training:
  - Backpropagation with gradient descent to update weights.
  - Loss Function: Mean Squared Error minimized d to improve forecast accuracy.
  - Early stopping to prevent overfitting
  - Epochs: 50 iterations over the dataset.
- Forecasting:
  - Recursive Strategy with 14-day window, spanning 7 months (May to November inclusive)



Source: https://vitalflux.com/sklearn-neural-network-regression-example-mlpregressor/

Model specifics: TDNN

- Architecture:
  - Input Layer: processed and scaled weather data
  - Hidden Layers: Two layers with 128 and 64 neurons respectively, using ReLU activation functions to introduce non-linearity.
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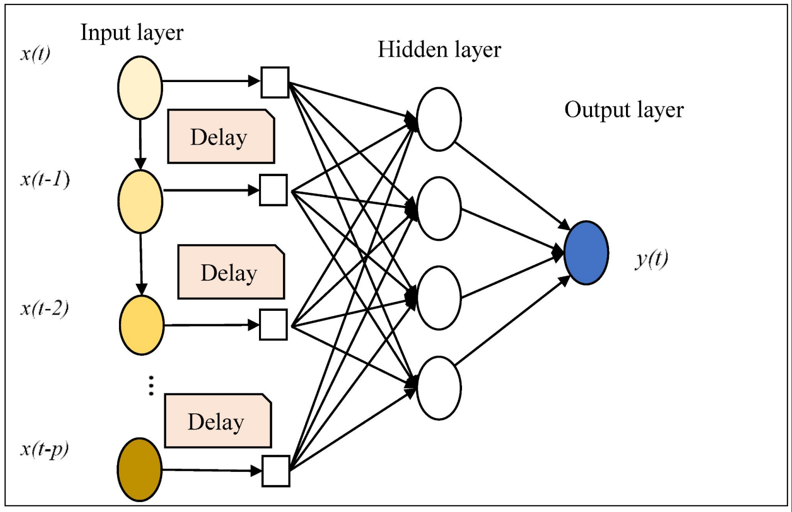


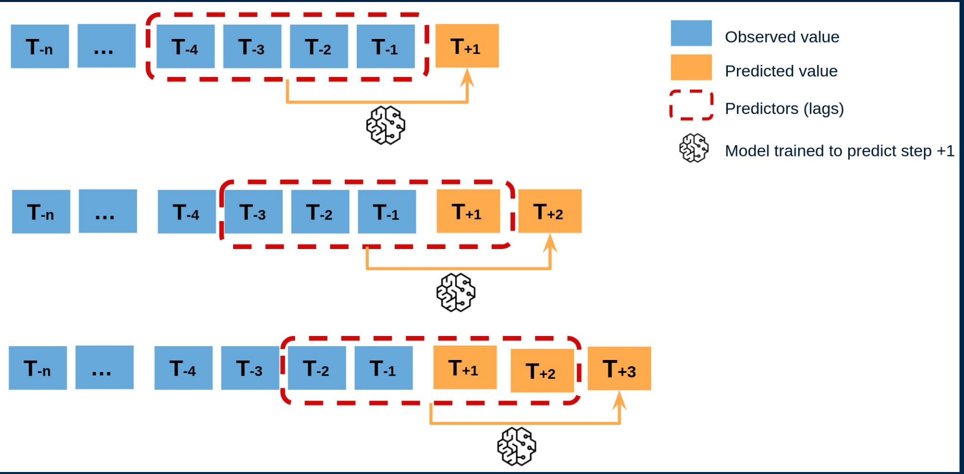
Source:
https://www.mdpi.com/2227-7390/7/10/959/htm

Forecasting Method

Recursive Forecasting with Rolling Window

Process:

1. Initial Forecasting Window: model initially provided with a set window of historical data (e.g., 30 days) to predict the subsequent time step.
2. Sequential Predictions: As each new forecast is generated, it becomes part of the input window, effectively "rolling" the window forward.
3. Iterative Approach: This process is repeated, with the model recursively using its own predictions as part of the input for future forecasts.



Source:
https://skforecast.org/0.9.1/user_guides/autoregresive-forecaster

Forecasting Method

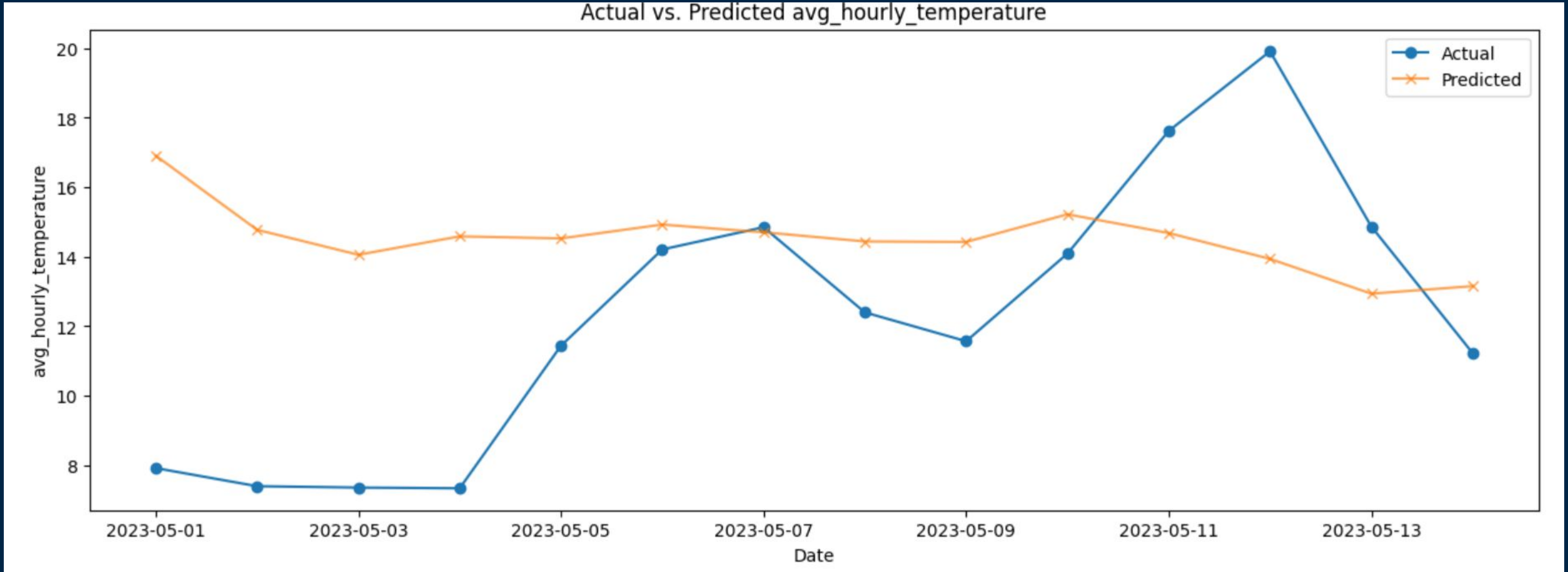
Advantages:

- Dynamic Updates: dynamically incorporates recent predictions, adapting to potential shifts in patterns as new data is forecasted.
- Consistent Input Structure: Ensures the model always receives input of consistent shape and size

Challenges:

- Error Propagation: Initial errors can compound over time, potentially leading to drift in longer-term forecasts.
- Dependency on Model Accuracy: Quality of the forecast relies heavily on the model's ability to make accurate short-term predictions.

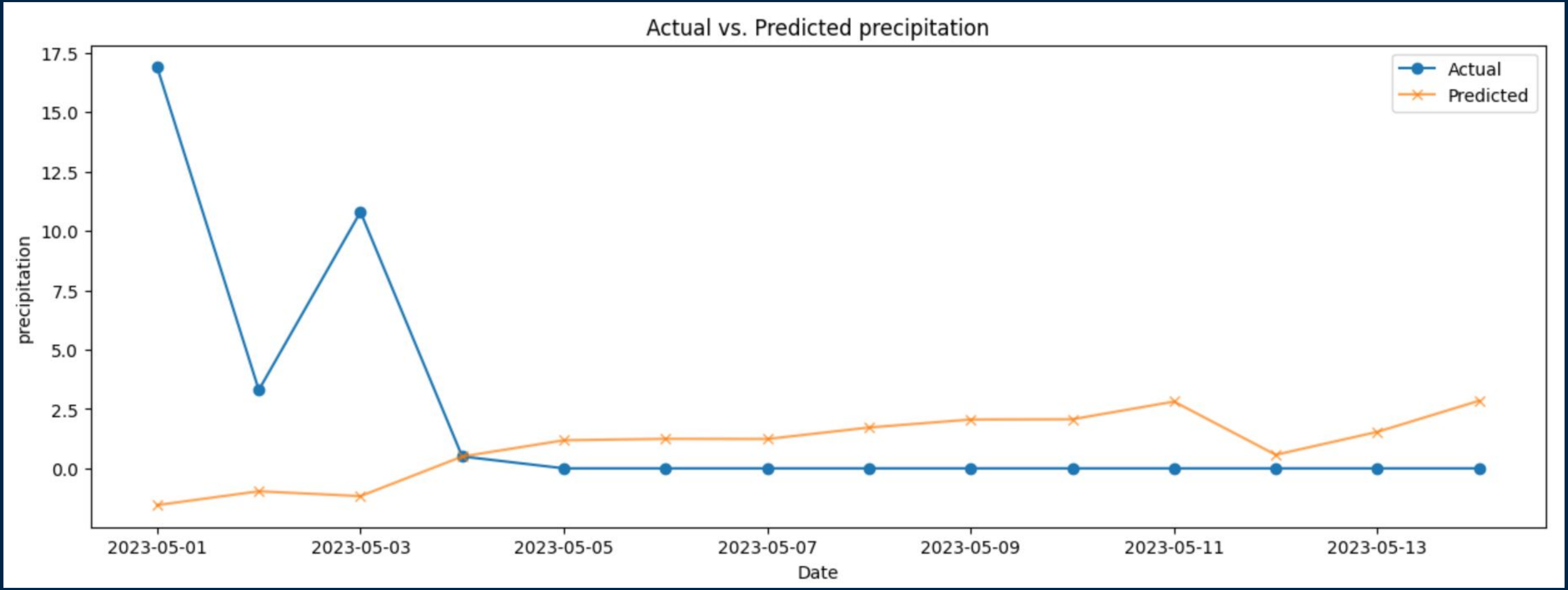
Results (MLP)



MAE: 3.79

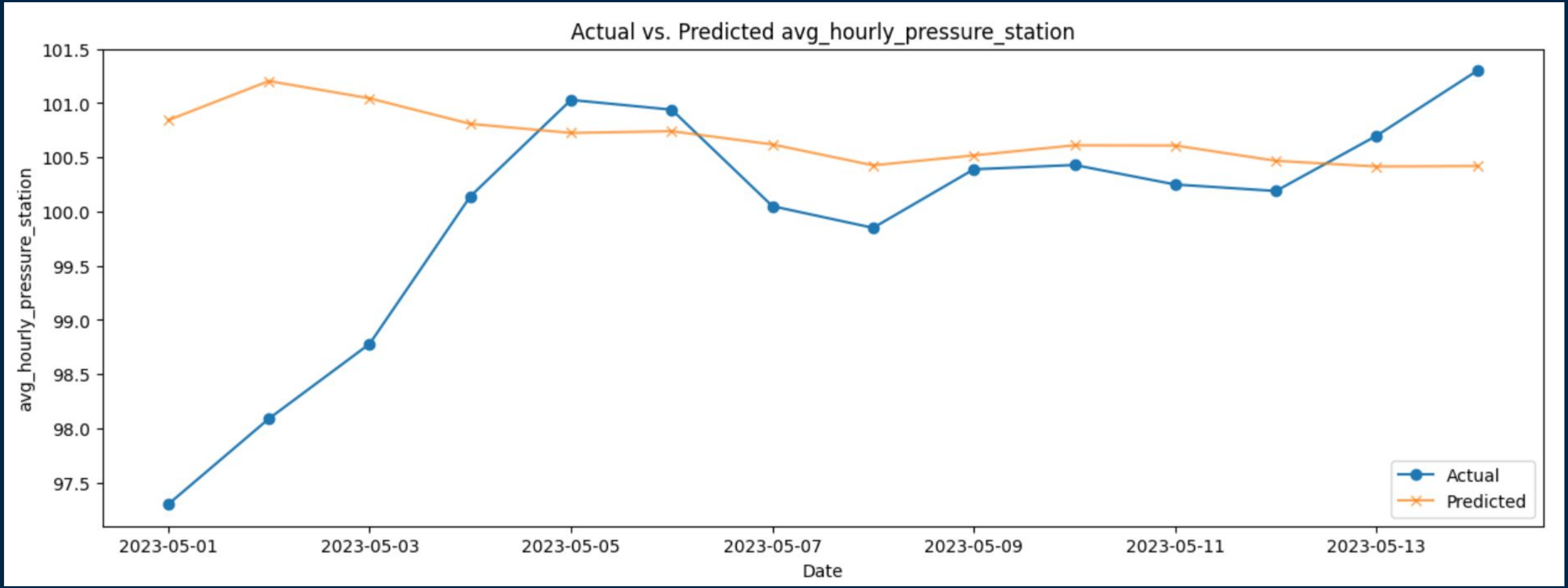
RMSE: 4.69

Results (MLP)



MAE: 3.71 RMSE: 6.19

Results (MLP)

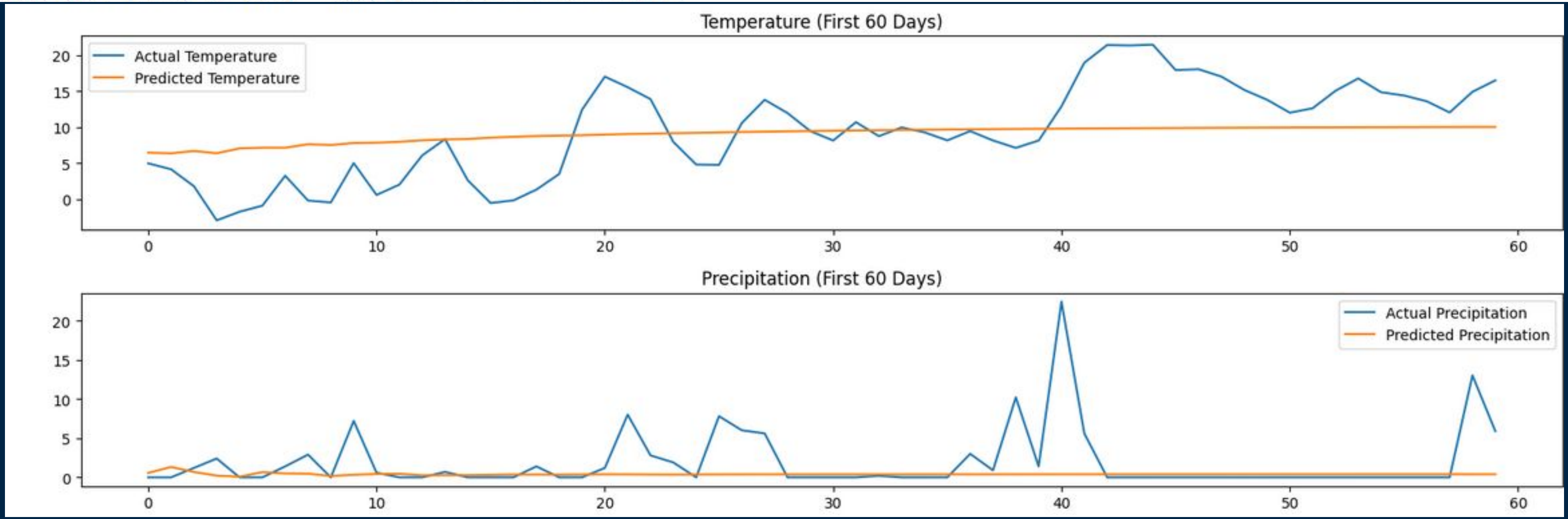


MAE: 0.95

RMSE: 1.45

Results (TDNN)

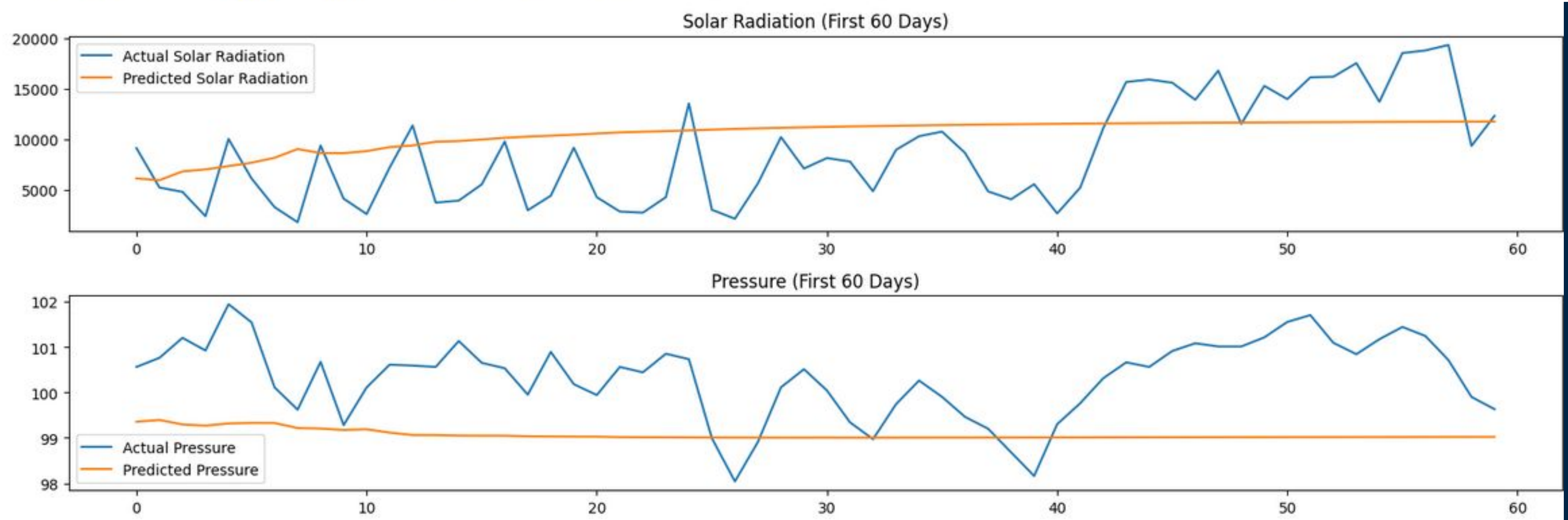
```
Temperature (First 60 Days) - Mean Absolute Error: 4.7349
Temperature (First 60 Days) - Root Mean Square Error: 5.6796
Precipitation (First 60 Days) - Mean Absolute Error: 1.9873
Precipitation (First 60 Days) - Root Mean Square Error: 4.1903
```



Temperature	MAE: 5.18	RMSE: 35.74
Precipitation	MAE: 1.22	RMSE: 4.43

Results (TDNN)

```
Solar Radiation (First 60 Days) - Mean Absolute Error: 4251.4069
Solar Radiation (First 60 Days) - Root Mean Square Error: 4913.9657
Pressure (First 60 Days) - Mean Absolute Error: 1.3387
Pressure (First 60 Days) - Root Mean Square Error: 1.5103
```




```
Zoomed-in MAEs: [4.734891268730164, 1.9872633881121875, 4251.406901041667, 1.3386918538411468]
Zoomed-in RMSEs: [5.679555111885503, 4.190339691454658, 4913.965660437872, 1.5103409517725992]
```

S. Radiation	MAE: 4251.41	RMSE: 1.34
Pressure	MAE: 4913.97	RMSE: 1.51

Answer to main questions

~~Capabilities:~~

1. ~~Prediction time frame~~

~~How many days into the future can the model predict accurately within an accuracy of 2 standard deviations?~~

2. ~~Prediction attributes~~

~~Which features can the model properly predict?~~

Challenges

- Data-Related Challenges
  - Missing or Incomplete Data
  - Noisy and Non-Stationary Data
  - High Dimensionality
- Model-Related Challenges
  - Model Selection and Complexity
  - Capturing Temporal Dependencies
- Computational Challenges
  - Scalability and Performance
  - Real-time Prediction Requirements
- Interpretability and Validation Challenges
  - Model Explainability
  - Validation and Trust
- Environmental and External Challenges
  - Micro-climate Specificity
  - Adapting to Climate Change

Conclusion and future work

We deployed two deep learning models to predict micro-climate using recursive forecasting technique in order to get prediction for the next 14 days based on a 3 day initial window of actual data. Based on our results our two models can confidently establish an acceptable prediction up to two weeks. Comparing to other deep learning models our numbers are impressive.

- Modifying window size and starting date in recursive forecasting
- More complex model, e.g. RNN, LSTM
- Hybridized prediction technique
- Modifying model features
  - (e.g. humidity, wind)

Q&A

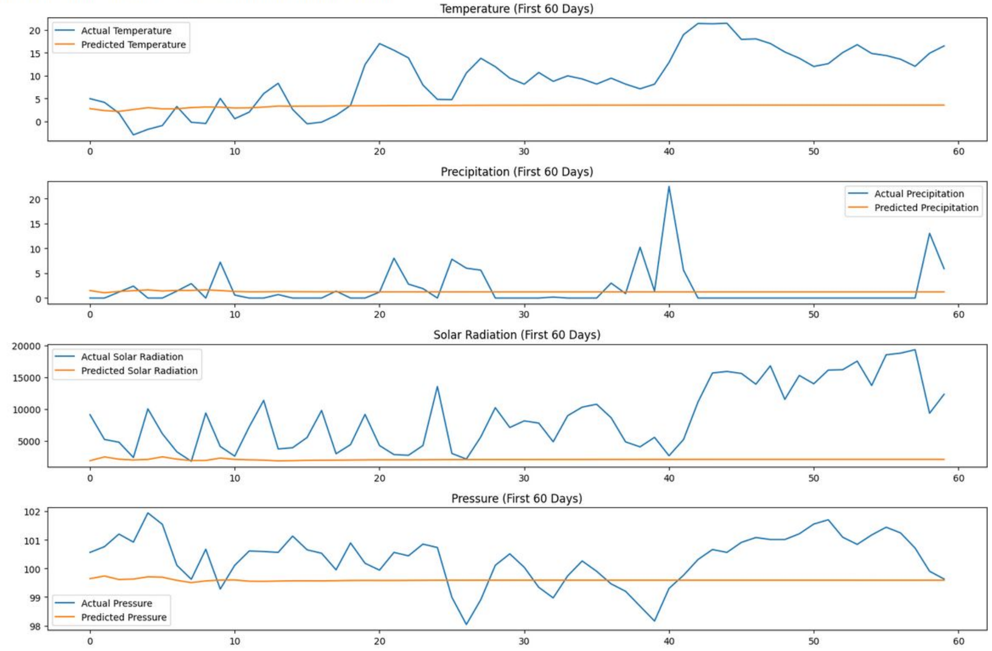
We are happy to answer your questions

Thanks!

Appendices: Other results of TDNN with modified parameters

Window size: 14 days
Learning rate: 1e-4

```
Temperature (First 60 Days) - Mean Absolute Error: 7.2478
Temperature (First 60 Days) - Root Mean Square Error: 8.7141
Precipitation (First 60 Days) - Mean Absolute Error: 2.2430
Precipitation (First 60 Days) - Root Mean Square Error: 3.9560
Solar Radiation (First 60 Days) - Mean Absolute Error: 6714.3309
Solar Radiation (First 60 Days) - Root Mean Square Error: 8402.9395
Pressure (First 60 Days) - Mean Absolute Error: 0.9761
Pressure (First 60 Days) - Root Mean Square Error: 1.1196
```




```
Zoomed-in MAEs: [7.247772327899933, 2.2430275170008342, 6714.330944824219, 0.976081924438477]
Zoomed-in RMSEs: [8.714114502703493, 3.9559963075098175, 8402.939463096973, 1.1195966367525285]
```

```
Mean Absolute Error: 3597.9146
Root Mean Square Error: 8277.4434
Temperature - Mean Absolute Error: 12.4467
Temperature - Root Mean Square Error: 13.6365
Precipitation - Mean Absolute Error: 2.9687
Precipitation - Root Mean Square Error: 6.3638
Solar Radiation - Mean Absolute Error: 14375.5380
Solar Radiation - Root Mean Square Error: 16554.8799
Pressure - Mean Absolute Error: 0.7050
Pressure - Root Mean Square Error: 0.8720
```