Improving Precipitation Estimates from Commercial Microwave Links Using Deep Learning: A Comparative Study on OpenMRG Data

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Introduction

Opportunistic Sensing is a widely acknowledged method capable of providing reliable operational precipitation observations and facilitate their use in precipitation nowcasting and operational hydrological forecasts.

Compared to conventional methods, Commercial Microwave Links (CMLs) offer great spatial and temporal resolution, making them a viable opportunistic sensing technology for precipitation assessment. However, noise, ambiguity, and non-linear connections between signal attenuation and rainfall intensity make it difficult to reliably estimate precipitation using CML-derived attenuation data.

Our Work

Comparative Study

In this work, we use the OpenMRG dataset, which contains metadata like frequency, link length, and polarization combined with CML-derived signal attenuation data, to investigate the potential of deep learning (DL) techniques to enhance precipitation estimations.

This analysis shows that both classical and quantum approaches can effectively model microwave link attenuation, with quantum methods showing particular promise.

Materials

From the netCDF format of CML Data, we get the RSL (Received Signal Level) and TSL (Transmitted Signal Level). We get the link characteristics like frequency, length, polarization, etc. from the metadata.

To estimate the effect of precipitation we calculate the attenuation by the difference between the TSL and RSL, similar method has been used by Ostrometzky & Eshel et al. where they determined the attenuation in each 15-min period as the difference between maximum TSL value and the minimum RSL value in that period. We use the given RSL and TSL of our dataset instead of the maximum and minimum.

	Frequency_GHz	Length_km	Polarization	Attenuation_dB
0	28.2065	0.69144	Vertical	56.963014
1	29.2145	0.69144	Vertical	56.942049
2	38.5280	0.61455	Vertical	56.890636
3	37.2680	0.61455	Vertical	56.937269
4	38.5280	0.32374	Vertical	56.949653

Fig 1. Partial Dataset

Methods

In order to compare our proposed model, we have used 6 other models, all of which had simple architectures:

- Random Forest Regressor
- LSTM (Long Short-Term Memory)
- XGBoost
- Support Vector Regression (SVR)
- k-Nearest Neighbors (k-NN)
- Elastic Net

Our proposed models:

- Stacking (Decision Tree + SVR)*
- Quantum Machine Learning (QML)*

Ensemble Learning (Stacking)

Stacking works by training several different base models — in our case, a Decision Tree Regressor and a Support Vector Regressor. Once they've learned their individual patterns, their predictions are used as new input features for a second-level model, known as the meta-learner. For this, we used a simple Linear Regression model. The meta-model learns to combine the strengths of the base models by finding the best way to weight their predictions.

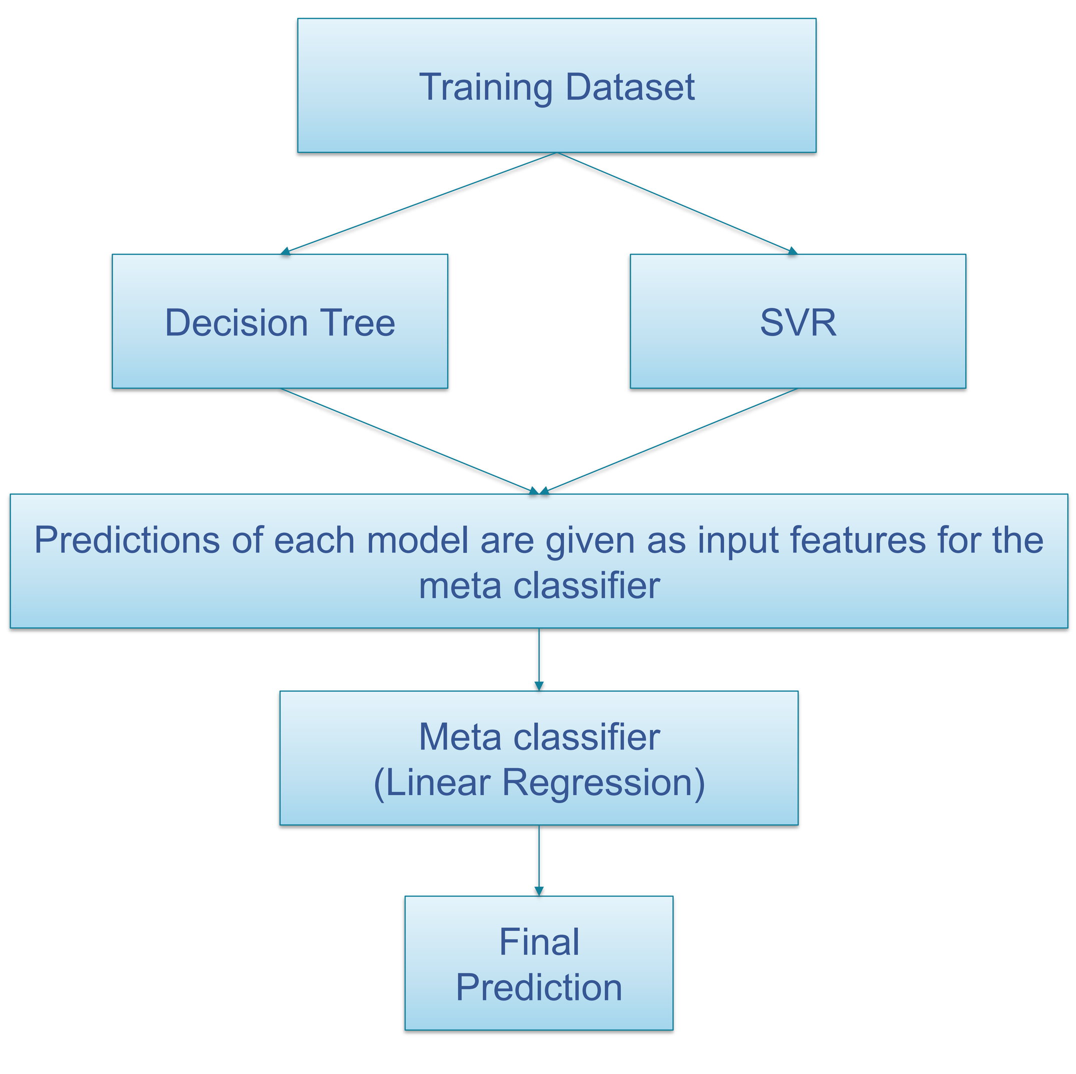

Fig 2. Ensemble Learning – Stacking architecture

Proposed QML Model

We built a quantum machine learning model using PennyLane. The goal was to predict signal attenuation based on three input features: frequency, length, and polarization. We used a hybrid approach, combining classical preprocessing with a quantum circuit.

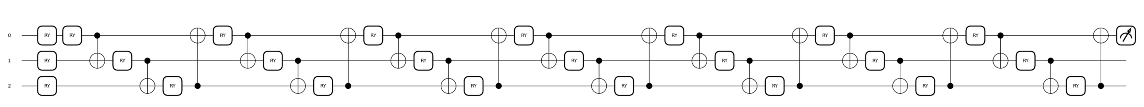

Fig 3. QML Circuit Design

Proposed QML Model

We designed a parameterized quantum circuit. This circuit uses three qubits—one for each input feature—and applies angle encoding using RY gates. The classical input data is encoded as rotation angles, which effectively maps each input vector into a quantum state. The heart of the model is a layered quantum circuit. We applied seven layers of parameterized RY gates followed by CNOT gates to introduce entanglement.

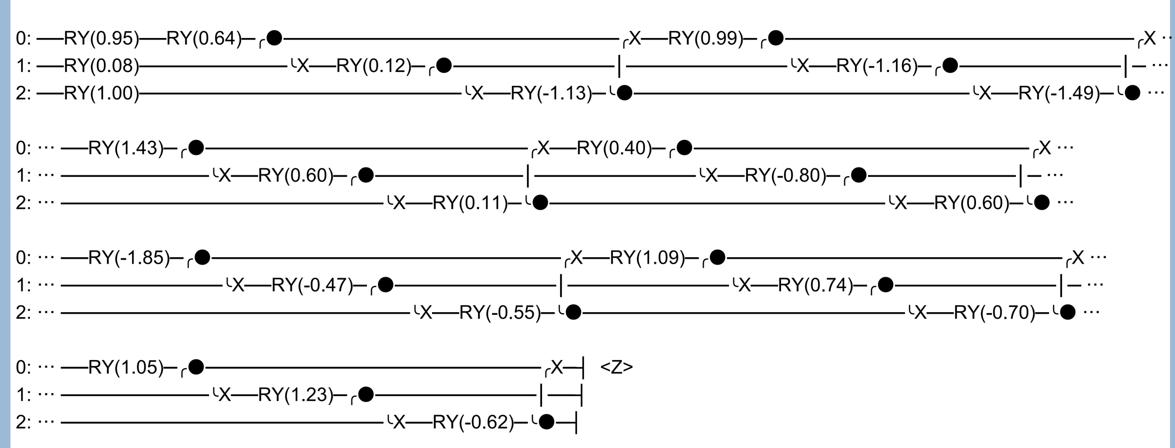

Fig 4. Circuit Structure with gate values

To monitor and analyze the training performance of the quantum machine learning model using a cost function (Mean Squared Error).

<u>Training Details</u>:
Optimizer: Gradient Descent
Steps: 100 iterations
Cost Function: Mean Squared Error (MSE)
Framework: PennyLane

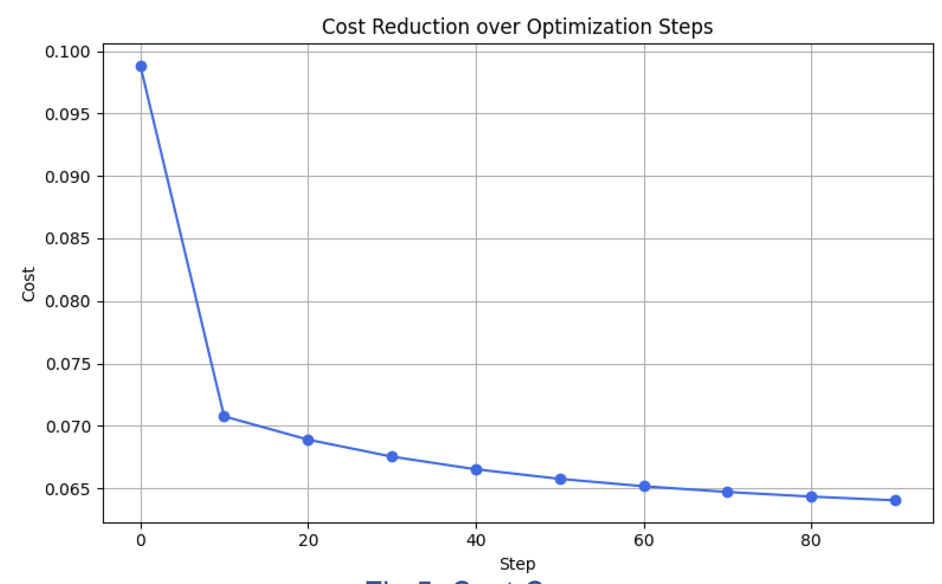

Fig 5. Cost Convergence

Performance Comparison

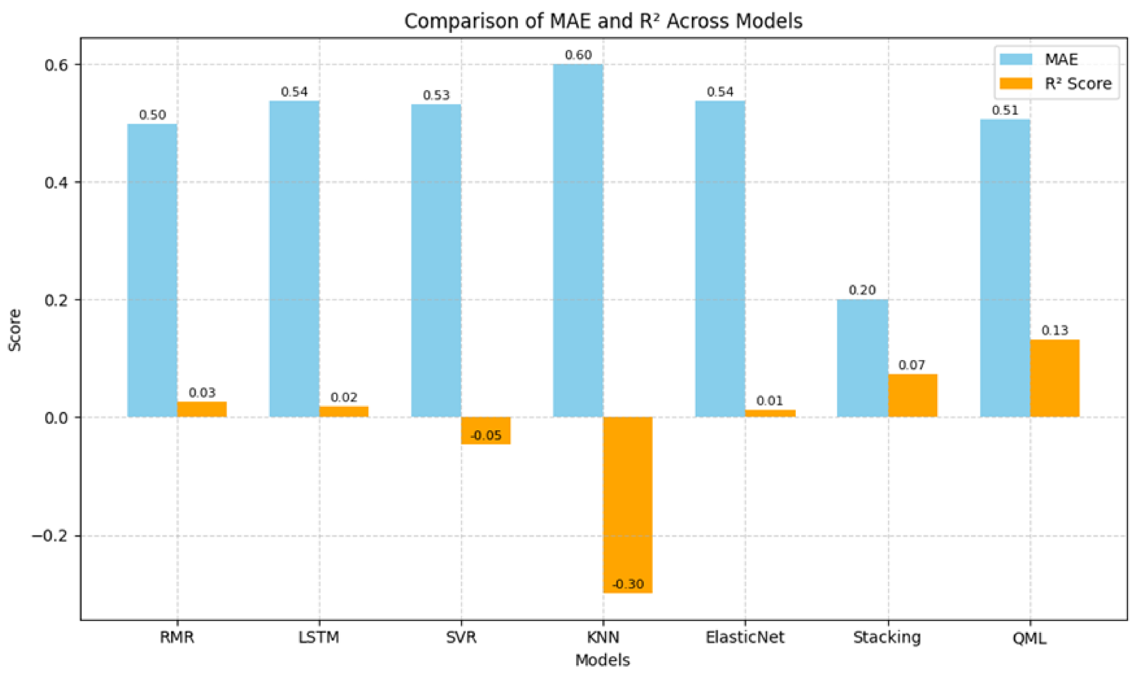

Fig 6. Comparison of Model performances

Conclusion

In order to promote the use of CMLs for real time, high-resolution precipitation monitoring, this work attempts to close the gap between data collection and useful insights. We showcase the efficiency of ensemble learning and Quantum Machine Learning approaches for processing CML data, this work adds to the expanding corpus of research on opportunistic sensing.