A Spatio-Temporal Deep Learning Approach for Radar-Based Quantitative Precipitation Estimation

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Abstract

Rain gauges and weather radars are the most widely used instruments for near real-time precipitation estimation. While rain gauges provide direct, point-wise measurements of ground-level rainfall rates, their spatial coverage is sparse. Furthermore, they are prone to various errors and uncertainties—such as shadowing from nearby objects or missing data—which can limit their operational utility. Conversely, weather radars offer superior spatial coverage and high resolution over broad areas, though they only provide indirect rainfall estimates. However, classical methods that rely on measurements from one or both systems—such as Z-R relationships, Kriging, or Kriging with External Drift (KED)—fail to leverage the temporal evolution of these phenomena, often resulting in inaccurate estimations of extreme weather events.

In this work, we propose a novel deep learning approach for radar-based Quantitative Precipitation Estimation (QPE). Leveraging the characteristics of residual networks and the U-Net architecture, we developed a new deep learning model capable of effectively extracting spatio-temporal features from time series of volumetric radar data to generate accurate rain-rate maps. The model is equipped with (3+1)D convolutional blocks, which separate spatial convolutions from temporal convolutions and introduce an additional non-linearity—an approach that has been demonstrated to yield superior performance in computer vision tasks. The model was trained and tested on a temporally synchronized dataset comprising multi-level CAPPI radar reflectivity fields from the Italian weather radar network and ground rain gauge measurements. The model's performance was evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Bias, and Correlation Index. Finally, the model was benchmarked against classical QPE methods, i.e., various Z-R relationships, Kriging, and the KED method.

Results highlight that a deep learning approach can outperform classical QPE methods. Leveraging the temporal characteristics of extreme weather events is fundamental in such applications, and recent developments in artificial intelligence must be integrated into future approaches to this type of problem, particularly from an operational perspective.