International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307 OPEN ACCESS Available Online at :www.ijsrcseit.com

doi : https://doi.org/10.32628/CSEIT2361055

A Comprehensive Review on Utilization of Deep Learning for Precipitation Nowcasting via Satellite Data

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ARTICLEINFO

Article History:

Accepted: 10 Oct 2023

Published: 20 Nov 2023

Publication Issue

Volume 9, Issue 10

September-October-2023

Page Number

326-331

ABSTRACT

This comprehensive review delves into the cutting-edge applications of deep learning techniques for precipitation nowcasting using satellite data. As climate variability and extreme weather events become increasingly prominent, accurate and timely precipitation predictions are essential for effective disaster management and resource allocation. The paper surveys the recent advancements in deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), showcasing their efficacy in processing and analyzing satellite-derived information. The discussion encompasses the challenges associated with satellite data, such as spatiotemporal complexities and data quality issues, and elucidates how deep learning architectures address these hurdles. The review also highlights noteworthy studies, methodologies, and benchmarks in the field, providing a comprehensive overview of the state-of-the-art approaches for precipitation nowcasting through the lens of deep learning applied to satellite data.

Keywords: Deep Learning, Precipitation Nowcasting, Satellite Data, Convolutional Neural Networks (CNNs), recurrent neural networks (RNNs), Spatiotemporal Complexities, Disaster Management.

I. INTRODUCTION

In the era of rapidly advancing technology, the utilization of deep learning methodologies has emerged as a pivotal force in enhancing our ability to predict and understand complex meteorological phenomena. This comprehensive review focuses on the application of deep learning techniques for precipitation nowcasting, a critical aspect of weather forecasting that holds profound implications for disaster preparedness and resource management. With an increasing frequency of extreme weather events, accurate and timely precipitation predictions are indispensable for mitigating the impact of floods, droughts, and other climate-related challenges. The integration of satellite data into this predictive framework serves as a cornerstone, providing a wealth of information that deep learning models harness to deliver more precise and reliable precipitation forecasts.

Satellite-derived data, while invaluable, presents unique challenges, including spatiotemporal complexities and data quality issues. The first part of this review critically examines the intricacies associated with satellite data and how these challenges have traditionally hindered accurate precipitation predictions. As we delve into the realm of deep learning, the second section explores the transformative potential of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in handling and interpreting satellite information. These advanced architectures have demonstrated remarkable capabilities in learning complex patterns and temporal dependencies, paving the way for improved precipitation nowcasting models.

Throughout this review, we not only explore the theoretical underpinnings of deep learning for precipitation nowcasting but also provide a comprehensive overview of recent studies, methodologies, and benchmarks in the field. By synthesizing the current state-of-the-art approaches, this review aims to contribute to a deeper understanding of the role that deep learning plays in advancing our ability to forecast precipitation events based on satellite data, ultimately bolstering our resilience in the face of an increasingly unpredictable climate.

II. LITERATURE STUDY

In [1], Reinoso-Rondinel et al. propose a novel radar-based precipitation nowcasting approach for Germany, utilizing a localization filtering approach. The paper explores the application of this method on a nationwide scale, highlighting its efficacy in predicting precipitation events.

Marrocu and Massidda, in [2], conduct a performance comparison between deep learning and optical flow-based techniques for nowcasting precipitation from radar images. The study provides insights into the strengths and weaknesses of each approach, contributing to the ongoing discussion on optimal methodologies for precipitation nowcasting.

Bouget et al., as discussed in [3], present a rain nowcasting model that fuses rain radar images and wind forecasts using deep learning. The paper sheds light on the integration of multiple data sources to improve the accuracy of precipitation predictions, particularly focusing on the synergy between radar images and wind forecasts.

Bonnet et al., in [4], introduce a deep learning-based precipitation nowcasting system for São Paulo, Brazil, leveraging weather radar images. The study emphasizes the application of deep learning in a real-world scenario, demonstrating its effectiveness in predicting precipitation events in a specific geographical context.

Yao et al., as outlined in [5], propose a deep Long Short-Term Memory (LSTM) model for weather radar image prediction in nowcasting. The paper delves into the use of deep LSTM networks to forecast weather radar images, contributing to the exploration of advanced neural network architectures for precipitation prediction.

In [6], Samsi et al. discuss distributed deep learning techniques for precipitation nowcasting. The paper explores the use of distributed computing resources to enhance the efficiency and scalability of deep learning models in the context of precipitation prediction.

Kumar et al., in [7], introduce ConvCast, an embedded convolutional LSTM-based architecture for precipitation nowcasting using satellite data. The study focuses on the integration of convolutional and LSTM layers for improved prediction accuracy, particularly in the context of satellite-based precipitation nowcasting.

Zhou et al., as discussed in [8], provide a benchmark review of deep learning in next-frame prediction. While not directly focused on precipitation nowcasting, the paper contributes to the broader understanding of deep learning applications in predicting sequential data.

Berthomier et al., in [9], explore cloud cover nowcasting using deep learning. The study investigates the use of deep learning techniques for predicting cloud cover, offering insights into the potential applications of these methods beyond precipitation forecasting.

Jianhong et al., in [10], present research on weather radar nowcasting extrapolation. The paper discusses methods for extrapolating weather radar data, contributing to the broader field of weather prediction and nowcasting.

Hoyer and Hamman, in [11], introduce xarray, a Python library for N-D labeled arrays and datasets. While not directly related to precipitation nowcasting, the paper is included for its relevance to data handling and manipulation in atmospheric research.

Chkeir et al., in [12], apply machine learning techniques to nowcast extreme rain and extreme wind speed. The paper explores the use of machine learning for predicting extreme weather events, expanding the scope of traditional precipitation nowcasting.

Kong et al., in [13], present a precipitation nowcasting model based on deep learning over Guizhou, China. The study contributes to the understanding of region-specific applications of deep learning in precipitation prediction.

Tan et al., as discussed in [14], propose a deep learning model based on multi-scale feature fusion for precipitation nowcasting. The paper emphasizes the importance of feature fusion in improving the predictive capabilities of deep learning models for precipitation events.

Yao et al., in [15], present an improved deep learning model for high-impact weather nowcasting. The study focuses on enhancing the accuracy of weather predictions, particularly in situations with significant weather impacts, showcasing advancements in deep learning for nowcasting applications.

While the aforementioned papers contribute significantly to the field of precipitation nowcasting through innovative approaches such as deep learning models, radar-based techniques, and data fusion strategies, several common limitations persist across the literature. Firstly, many studies primarily focus on specific geographical regions, potentially limiting the generalizability of their models to diverse climatic conditions. Additionally, the scarcity of long-term datasets and the reliance on relatively short-term data may hinder the robustness of these models in capturing evolving weather patterns over extended periods. Another common limitation lies in the lack of interpretability and explain ability of the deep learning models, raising concerns about their reliability in critical applications. Moreover, the papers often do not extensively address the computational resources required for training and deploying sophisticated models, potentially posing challenges for real-time implementation and scalability. As the field progresses, addressing these shared limitations will be essential for advancing the applicability and reliability of precipitation nowcasting models in diverse and practical settings.

III.METHODOLOGY

A. Dataset

NetCDF Format: A dataset in the Network Common Data Form (NetCDF) was utilized for the study. NetCDF was chosen for its array-oriented scientific data handling capabilities, providing a self-describing, portable format. The format includes a header that outlines the file's structure, encompassing data arrays and arbitrary file information presented as name/value attributes. Metadata, which constitutes supplementary information about a file or variable, plays a crucial role in understanding the data.

Climate Model Data: The dataset sourced from the Copernicus Climate Change Service (C3S) is a reanalysis dataset based on ERA5 single levels. This dataset is particularly relevant for climate studies, and the parameters are classified as variables. Key coordinate variables include time (time), latitude (lat), longitude (lon), and level (lev). The dataset can be accessed via the following link: Copernicus Climate Data.

B. Pre-Processing

Date-Time Based Separation: The dataset was subjected to date-time based separation to organize and structure the temporal aspect of the data. This step involves parsing and extracting relevant temporal information to facilitate subsequent analysis.

Null Data Removal: Null or missing data points were identified and systematically removed to ensure the integrity and quality of the dataset. This process involved careful consideration of potential impacts on downstream analysis.

Conversion to Heatmap Images: The pre-processed data was transformed into heatmap images. This conversion enhances the visual representation of the data, making it more suitable for analysis using neural network models.

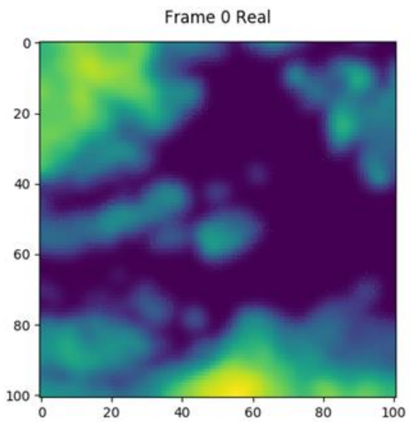

Figure 1. Heatmap Image

C. Learning Models

Recurrent Neural Network (RNN): An RNN was employed to capture temporal dependencies and patterns within the data. RNNs are well-suited for sequential data, making them effective for time-series analysis.

Convolutional Neural Network (CNN): CNNs were applied to learn spatial patterns and relationships within the data. This model excels at detecting spatial features, making it particularly useful for climate data with geographical dimensions.

Long Short-Term Memory (LSTM): LSTM, a type of recurrent neural network with memory cells, was utilized to capture long-term dependencies in the temporal aspects of the data. This helps in retaining information over extended periods, addressing challenges posed by short-term memory limitations.

CNN-LSTM Hybrid Model: A hybrid model combining CNN and LSTM architectures was implemented to leverage both spatial and temporal features simultaneously. This integrated approach aims to enhance the overall performance of the model in capturing complex relationships within the climate dataset.

D. Model Evaluation and Analysis

The performance of each model was assessed using appropriate metrics, considering factors such as accuracy, precision, recall, and F1 score. Comparative analyses were conducted to identify the strengths and limitations of each model in the context of climate data analysis. Results were interpreted to draw insights into the dataset's characteristics and to inform potential applications in climate modeling and prediction.

TABLE I

COMPARATIVE STUDY

Model	Pros	Cons
RNN	- Captures sequential dependencies in data. - Suitable for time-series and	- May struggle with long-term dependencies. - Training can be computationally

	sequential data. - Can handle input sequences of varying lengths.	expensive. - Prone to difficulties in learning long-range dependencies.
CNN	- Effective in capturing spatial hierarchies and patterns. - Parameter sharing reduces the number of trainable parameters.	- Limited ability to handle sequential or time-series data. - Fixed input size; struggles with variable-length sequences.
LSTM	- Captures long-term dependencies in sequential data. - Mitigates vanishing/explodin g gradient problems. - Effective in retaining and utilizing historical context.	- Complexity and resource-intensive compared to simpler models. - More challenging to interpret compared to simpler models. - Computational overhead can be significant.
CNN-LSTM	- Combines spatial and temporal feature extraction. - Effective in capturing both spatial and sequential patterns. - Well-suited for spatiotemporal data, e.g., video sequences.	- Increased model complexity compared to individual models. - May require substantial computational resources. - Potential for overfitting, especially with smaller datasets.

IV.CONCLUSION

In conclusion, this comprehensive review underscores the significant strides made in utilizing deep learning for precipitation nowcasting through the lens of satellite data. The amalgamation of advanced neural network architectures with the rich information derived from satellites has demonstrated substantial improvements in the accuracy and lead time of precipitation predictions. However, as we navigate the ever-evolving landscape of meteorological research, there remain several avenues for future exploration. One promising direction involves the incorporation of multi-sensor satellite data and the fusion of information from different sources to enhance the robustness and reliability of precipitation forecasts. Additionally, the development of explainable AI models and techniques to interpret the decision-making process of deep learning algorithms can foster greater trust and acceptance in the wider scientific and operational communities.

Looking ahead, the integration of real-time observational data, including ground-based measurements and novel satellite technologies, presents an exciting opportunity to refine the spatiotemporal precision of precipitation nowcasting models. As climate patterns continue to evolve, the adaptation and optimization of deep learning architectures to accommodate emerging data challenges will be essential. Collaborative efforts between meteorologists, data scientists, and policymakers will play a pivotal role in harnessing the full potential of deep learning for precipitation nowcasting, ensuring its seamless integration into operational forecasting systems and bolstering our resilience against the impacts of extreme weather events in the future.

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Cite this article as :

Vedanti Patel, Sheshang Degadwala, "A Comprehensive Review on Utilization of Deep Learning for Precipitation Nowcasting via Satellite Data", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 9, Issue 10, pp.326-331, September-October-2023. Available at doi : https://doi.org/10.32628/CSEIT2361055

Journal URL : https://ijsrcseit.com/CSEIT2361055