RADemics

Predictive Climate Analytics Using Deep Learning and Edge IoT Networks

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Abstract

Rapid environmental changes and the increasing frequency of extreme climate events necessitate predictive frameworks capable of delivering accurate, timely, and localized forecasts. Integration of deep learning with edge-enabled Internet of Things (IoT) networks presents a transformative approach for climate analytics by combining advanced computational intelligence with distributed sensing infrastructures. Edge computing facilitates low-latency data processing, on-site inference, and energy-efficient model deployment, enabling near-real-time prediction of temperature variations, precipitation patterns, air quality indices, and extreme weather events. Distributed deep learning strategies, including federated and decentralized learning, enhance scalability and privacy while maintaining predictive accuracy across heterogeneous sensor networks. Model optimization techniques, such as pruning, quantization, and knowledge distillation, enable deployment on resource-constrained devices without compromising performance. Comprehensive evaluation of latency, energy consumption, communication efficiency, and prediction reliability ensures practical applicability in real-world environmental monitoring. The chapter further identifies existing research gaps and outlines future directions for developing robust, adaptive, and interpretable climate prediction systems that support decision-making and risk mitigation.

Keywords: Predictive Climate Analytics, Deep Learning, Edge Computing, IoT Networks, Real-Time Forecasting, Distributed Systems

Introduction

Rapid environmental changes, increasing global temperatures, and the heightened frequency of extreme weather events have amplified the need for advanced predictive systems capable of providing accurate, real-time climate forecasts [1], [2]. Traditional numerical and statistical climate models, while effective for long-term projections, often struggle to deliver high-resolution, location-specific predictions [3]. Limitations arise from high computational complexity, coarse spatial granularity, and reliance on centralized processing infrastructures [4]. In contrast, data-driven approaches leveraging dense sensor networks and artificial intelligence can address these gaps by capturing complex spatio-temporal dependencies and providing actionable insights for various applications, including disaster management, urban planning, agriculture, and public health [5].

The proliferation of Internet of Things (IoT) technologies has enabled widespread deployment of environmental monitoring devices across urban, rural, and remote areas [6]. These sensor networks continuously capture data on temperature, humidity, rainfall, wind speed, solar radiation, and air quality, generating high-volume, heterogeneous datasets [7]. Effective utilization of this data requires real-time collection, preprocessing, and storage mechanisms, as well as intelligent strategies to handle sensor noise, missing values, and variability in data quality [8]. IoT networks offer flexible, scalable infrastructure that supports both centralized and distributed computing approaches, creating opportunities for enhanced predictive performance while maintaining operational efficiency [9], [10].

Integration of deep learning techniques with IoT networks allows for modeling of highly non-linear and dynamic climate phenomena [11]. Neural network architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and transformer models provide the ability to extract meaningful patterns from large-scale spatio-temporal datasets [12]. These architectures capture interdependencies across time and space, enabling accurate forecasting of temperature fluctuations, precipitation events, air quality changes, and other critical environmental variables [13]. Model optimization techniques, including pruning, quantization, and knowledge distillation, allow deployment on resource-constrained devices without compromising predictive accuracy [14], [15].