A Hybrid Approach to Climate Prediction: Physics-Informed Neural Networks for Accurate Temperature Forecasting in Bangladesh

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***Abstract*—This paper presents a novel approach to improving daily temperature forecasting in Bangladesh, a country highly vulnerable to climate change. We propose the use of Physics-Informed Neural Networks (PINNs), a hybrid model that integrates domain-specific seasonal knowledge with machine learning techniques. By embedding physical constraints such as the annual temperature cycle, our model ensures that predictions are both data-driven and physically consistent. Using a large dataset from 35 meteorological stations across Bangladesh, the PINN is trained to predict daily temperature, incorporating key weather features such as humidity, rainfall, and sunshine. The model's performance is evaluated against conventional machine learning methods, demonstrating a significant reduction in prediction error and a robust ability to capture the underlying seasonal temperature patterns. The results show an R^2 value of 0.87 and an RMSE of 1.53°C, indicating that the PINN outperforms traditional models in both accuracy and stability. This study highlights the potential of PINNs for climate risk management, offering an accurate and interpretable tool for improving agricultural decision-making, disaster preparedness, and policy planning in Bangladesh. Future work will focus on enhancing the model's robustness through the inclusion of additional climate variables and more diverse data sources. The code is available on GitHub:**

***Index Terms*—Physics-Informed Neural Networks, Temperature Forecasting, Climate Change, Machine Learning, Bangladesh, Climate Risk Management, Seasonal Knowledge, Hybrid Models.**

I. Introduction

Climate change has become a pressing global concern, marked by rising average temperatures and more frequent climatic extremes essd.copernicus.org. Recent data indicate that human-induced warming now exceeds 1°C above pre-industrial levels essd.copernicus.org, an unprecedented rate that underscores the urgency of climate action. Importantly, the impacts of this global trend are not uniform; regional vulnerabilities and climate sensitivities dictate how severely different communities are affected.

Bangladesh stands out as particularly vulnerable to climate variability due to its unique geography and socioeconomic factors. The country's low-lying deltaic terrain, monsoon-dominated climate, and high population density make it prone to natural hazards such as floods, droughts, and cyclones, rendering it one of the most climate-risk-exposed nations (1). Indeed, Bangladesh consistently ranks among the worst-affected countries by extreme weather events despite contributing only a marginal share of global greenhouse gas emissions (2). In this context, improving the accuracy of weather predictions is not merely a technical pursuit but a societal necessity. Reliable forecasts – for example, daily temperature outlooks – are crucial for climate adaptation planning, agricultural decision-making, and disaster preparedness (3). Timely and precise meteorological information can help farmers optimize crop management and enable policymakers to implement early warning measures, thereby bolstering resilience in climate-sensitive sectors citeImamEtAl2024AgrometBangladesh.

Conventional numerical weather prediction (NWP) models remain the gold standard for forecasting but come with notable limitations. NWP relies on solving atmospheric equations; they've been highly successful but still suffer from incomplete representations of complex processes and heavy computational costs (4). Data-driven methods now complement NWP: ML—from classical regressions and SVMs to deep learning—learns from historical observations for temperature and rainfall, uncovering subtle relationships and enabling fast inference, though often as statistical "black boxes" lacking explicit scientific structure (4; 5; 6).

Purely data-driven models face limits: traditional statistical

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ML struggles with high-dimensional, nonlinear atmospheric dynamics (7); unlike first-principles NWP, they lack built-in physical constraints, risking violations of conservation laws and unrealistic outputs under shift (8; 9). They extrapolate poorly to changing regimes and rare extremes (10), and must learn seasonality from scratch; while Seasonal ARIMA embeds annual cycles (4; 11), standard neural networks may miss recurring monsoon-driven patterns without long histories or engineered seasonal inputs.

Physics-informed neural networks (PINNs) have emerged as a promising hybrid approach to bridge this gap. PINNs embed scientific knowledge (e.g. known laws or patterns) directly into a neural network's training objective (12). For example, the regular seasonal cycle of temperature can be encoded as a prior (via a harmonic oscillator representation of annual periodicity) within the model architecture (7; 12). By infusing such domain priors, the PINN ensures that predictions inherently respect well-established climate behaviors (like seasonality), which improves physical consistency. At the same time, the network retains the flexibility of a data-driven model to learn complex relationships from historical climate data.

Training a PINN on real-world climate observations – which are often noisy and involve natural variability – benefits greatly from modern stochastic optimization techniques. In particular, the Adam optimizer (a form of stochastic gradient descent) adapts the learning process to noisy gradients, aiding convergence on messy data (13; 14). Adam's adaptive moment estimation makes learning robust against fluctuations and local minima, which is crucial when fitting models to climate signals embedded in noise(13). The synergy between physics-guided modeling and robust stochastic optimization is key: the physical constraints guide the network to plausible solutions, while the optimizer efficiently tunes parameters even with noisy inputs.

In summary, the proposed approach leverages a PINN infused with seasonal climate priors and trained via adaptive stochastic optimization. This combination capitalizes on both scientific knowledge and data-driven learning. Such a framework is expected to yield more accurate, interpretable, and stable daily temperature predictions for Bangladesh, providing a valuable tool for climate risk management in this vulnerable region.

II. Related Work

Machine learning (ML) techniques have been applied to weather and climate prediction for decades. Traditional models like linear regression, support vector machines, and random forests capture basic patterns in historical data and have been used for tasks such as weather classification or single-variable forecasting (e.g. daily temperature or rainfall) (4). However, these methods rely on hand-crafted features and often fail to represent complex nonlinear interactions in climate systems, especially for high-dimensional inputs (4; 7). By contrast, deep learning models automatically learn spatiotemporal patterns, leading to improved accuracy in many climate forecasting tasks. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) – particularly Long Short-Term Memory (LSTM) networks – have been used for applications ranging from precipitation nowcasting to multi-factor weather prediction and extreme event detection (4).

Numerous studies worldwide demonstrate the promise of data-driven climate models. For example, a deep LSTM model outperformed a random forest in regional rainfall forecasting (5). Researchers in South Asia have likewise leveraged ML and DL for monsoonal climates: Narang et al. improved all-India summer monsoon rainfall predictions using ensemble regression techniques (4), while in Bangladesh Yaseen et al. accurately predicted drought indices (SPI) with models such as random forests and extreme learning machines (15). Hybrid approaches have also been explored – for instance, a stacked Bi-LSTM model improved seasonal rainfall prediction for drought management (16). Including multiple input variables can further boost accuracy: one model improved daily temperature forecasts by incorporating humidity, wind, and precipitation as features (17). These efforts show that ML/DL models can learn complex mappings for temperature, rainfall, humidity and other variables, often achieving high accuracy under normal conditions.

Despite these advances, purely data-driven models have notable limitations in climate applications. A key issue is the lack of physical constraints – models act as statistical "black boxes" that may ignore conservation laws or known dynamics (18). This can lead to physically inconsistent or non-generalizable outputs (18). Data-driven models also struggle to generalize across seasons and to predict extreme events. They tend to be tuned to average conditions and have difficulty extrapolating to rare extremes, partly because such events are scarce in training data (4). Moreover, most neural forecasting models do not explicitly encode periodic seasonal cycles, so performance can degrade when climate patterns shift (e.g. during monsoon onset or winter anomalies) (4).

To address these gaps, researchers have begun integrating scientific knowledge into neural network models. One promising avenue is physics-informed neural networks (PINNs), which embed governing equations or physical constraints into the learning process. For example, (19) used PINNs to solve the spherical shallow-water equations by enforcing the governing PDEs during training. Similarly, others have developed neural weather models that incorporate fluid-dynamics principles (e.g. advection continuity laws) directly into their networks (18), yielding forecasts that better conserve physical quantities. By blending data-driven learning with physical laws, these approaches can produce more realistic and interpretable predictions (4). Initial results are promising: physics-informed models better capture extremes and provide more stable long-range forecasts, though balancing data and physics remains challenging.

III. Methodology

A. Dataset & Preprocessing

We utilized a daily weather dataset from 35 meteorological stations across Bangladesh, covering multiple decades up to 2023 (543,839 records in total) (20). The data included daily rainfall (mm), sunshine (hours), humidity (%), and temperature (°C). As the dataset had no missing values, minimal preprocessing was required. We parsed the Year, Month, and Day fields into a single date and then extracted the day-of-year (1–365) for each record to serve as a seasonal indicator. We selected daily mean temperature as the prediction target, with input features consisting of humidity, rainfall, sunshine, and the day-of-year. All features and the target variable were standardized (zero mean, unit variance) before modeling to ensure comparability and improve training stability.

B. Feature Selection & Seasonal Encoding

The input feature set was chosen based on domain knowledge of climatic factors affecting temperature. We included key weather attributes – humidity, rainfall, sunshine – as they influence daily temperature variations, and added the day-of-year value to encode the seasonal context. This simple seasonal encoding provides the network with information about the time of year (e.g. pre-monsoon, winter) without explicitly adding multiple cyclic features. We did not incorporate station identifiers or long-term trend factors, instead training a unified model across all locations. The inclusion of day-of-year was especially important for integrating a physics-based seasonal prior, described next.

C. Neural Network Architecture

We developed a physics-informed neural network (PINN) model with a simple feed-forward architecture suitable for regression. The network is a fully-connected multilayer perceptron implemented in TensorFlow/Keras. It consists of an input layer corresponding to the 4 features (DoY, humidity, rainfall, sunshine), two hidden layers, and one output layer. Each hidden layer has `64 neurons` with `hyperbolic tangent (tanh)` activation functions. The tanh activation was chosen to introduce nonlinearity while keeping outputs bounded (approximately -1 to 1), which aligns well with the normalized data range. Having two hidden layers with a moderate width (64) allows the model to learn complex relationships between inputs and temperature without excessive complexity. The output layer is a single neuron with `linear activation`, producing the predicted temperature value (in normalized scale). We opted for a linear output so that the network can predict any value (positive or negative in standardized units) and this can be converted back to the actual temperature. The overall architecture can be summarized as: `Input(4) { Dense(64, tanh) { Dense(64, tanh) { Dense(1, linear)`. This configuration was found to be sufficient for modeling the temperature patterns in our data. All weights were initialized with default Xavier/Glorot initialization, and biases with zeros. The relatively shallow network (2 hidden layers) strikes a balance between flexibility and overfitting risk, given the large number of training samples.

D. Physics-Informed Loss Function

To inject domain knowledge about seasonal temperature behavior, we augmented the model's loss function with a physics-informed component. In physics-informed neural networks, known physical relationships or constraints are encoded as additional terms in the loss (21). In our case, the known "physics" is the approximate sinusoidal seasonal pattern of temperature over the year. We expect temperature $T(d)$ as a function of day-of-year d to follow a roughly sinusoidal curve with a one-year period. For example, temperatures should rise and fall in a smooth oscillatory manner, peaking in the summer months and bottoming out in winter. We formulate this prior expectation as:

$$T_{\text{seasonal}}(d) = \sin\left(\frac{2\pi d}{365}\right) \tag{1}$$

which is a unit-amplitude sinusoid of period 365 days. (When the network inputs are standardized, d is effectively scaled to a similar range, but conceptually this represents an annual cycle.) We then define a **physics residual** as the difference between the network's predicted temperature and this expected seasonal baseline:

$$r_{\text{phys}} = \hat{T}(d) - T_{\text{seasonal}}(d) \tag{2}$$

where $\hat{T}(d)$ is the model's predicted (normalized) temperature for day d. The physics-informed loss term is the Mean Squared Error of this residual, i.e. **Physics Loss** $L_{\text{phys}} = \text{MSE}(r_{\text{phys}}) = \mathbb{E}[(\hat{T}(d) - \sin(2\pi d/365))^2]$. This term penalizes the model if its predictions deviate significantly from a smooth sinusoidal curve as a function of the calendar day. Intuitively, it encourages the learned function $\hat{T}(d)$ to be close to sinusoidal – capturing the seasonal trend – even without seeing temperature data (this acts as a regularizer informed by climate knowledge). It is important to note that this "physics" is a simplification of reality (real temperature patterns are not perfectly sinusoidal), but it encodes the correct frequency (annual cycle) and general shape, thus providing a helpful prior for the network to follow. By incorporating this into the training objective, we guide the neural network to produce seasonally consistent predictions, improving generalization especially in data-sparse regimes or in preventing the model from learning spurious non-seasonal signals.

E. Total Loss Function

The overall loss function used to train the network is a weighted combination of the traditional data fitting loss and the physics-informed term. Specifically, we define the total loss L_{total} as:

$$L_{\text{total}} = L_{\text{data}} + \lambda\, L_{\text{phys}}, \tag{3}$$

where Data Loss L_{data} is the mean squared error between predicted and true temperatures (the usual supervised learning objective), and L_{phys} is the physics loss defined above. The hyperparameter λ controls the trade-off between adhering to the data and following the physical prior. In our experiments, we set $\lambda = 0.1$, meaning the physics term contributes 10% of the weight of the data term. This choice was made to gently regularize the model towards the sinusoidal behavior without overpowering the actual data – i.e., the model will primarily fit the observations but will be nudged towards the expected seasonal trend. We found this weighting to be reasonable for capturing the annual cycle while still letting

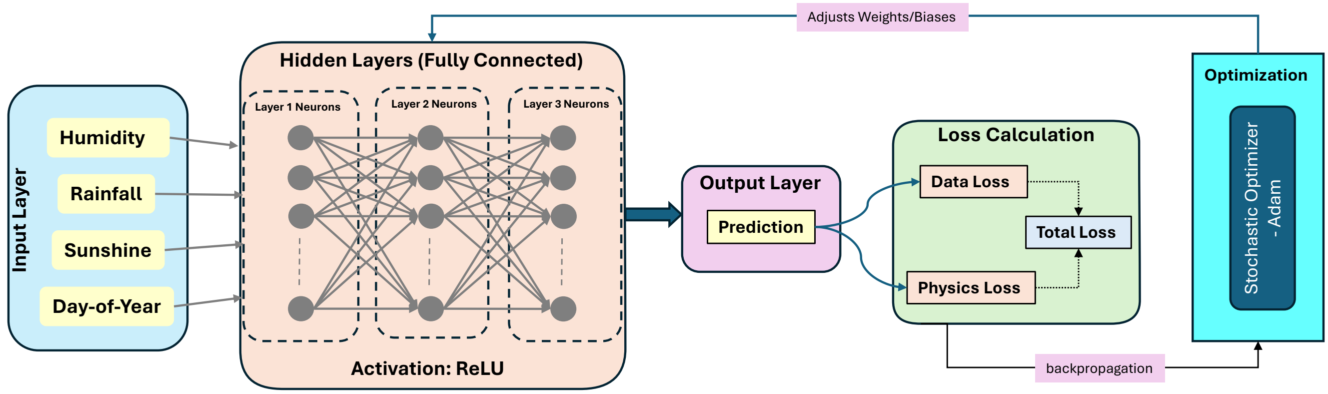

Fig. 1. PINN architecture for daily temperature forecasting, integrating meteorological inputs, physics-informed loss, and Adam optimization.. The figure depicts a Physics-Informed Neural Network (PINN) for daily temperature forecasting in Bangladesh. It processes meteorological inputs through three hidden layers and outputs temperature predictions. The Physics-Informed Loss ensures seasonal consistency, while the Adam optimizer adjusts the model's weights using both data and physics-based loss during training.

the network learn deviations due to weather events or long-term trends. During training, the custom loss is computed for each batch: the network predictions are compared to true values for MSE, and simultaneously the physics residuals are computed (using the DoY feature) for the sinusoidal MSE term. By minimizing L_{total}, the optimizer updates weights in a direction that compromises between reducing prediction errors and enforcing seasonal consistency. This PINN approach effectively injects domain expertise (the climate seasonality) directly into the learning process, which can improve model robustness and interpretability.

F. Model Training

We trained the network in TensorFlow 2.x using mini-batch stochastic gradient descent with the Adam optimizer (chosen for its adaptive learning rates and robust performance on large datasets). The learning rate was set to 0.001. Training ran for 100 epochs on GPU hardware with a batch size of 256, which provided a good balance between gradient stability and throughput for our data volume.

We split the data 80/20 into training and test sets ($\approx$435,000 samples for training; $\approx$109,000 for testing), stratified by time so all years were represented in both sets. After each epoch, we computed total loss on the hold-out set to monitor generalization. The training and validation loss curves remained closely aligned throughout, indicating stable learning without overfitting. Because validation loss either improved or plateaued through epoch 100, we did not apply early stopping and retained the final epoch's parameters as the deployed model.

IV. Result Analysis

The experiments draw on a large daily weather dataset encompassing 543839 entries from multiple meteorological stations across Bangladesh. Each record contains the day, month and year along with rainfall, sunshine hours, relative humidity and observed temperature. This rich dataset captures strong seasonal cycles—cooler, drier winters and hot, humid monsoon months—making it a rigorous test bed for data-driven climate models.

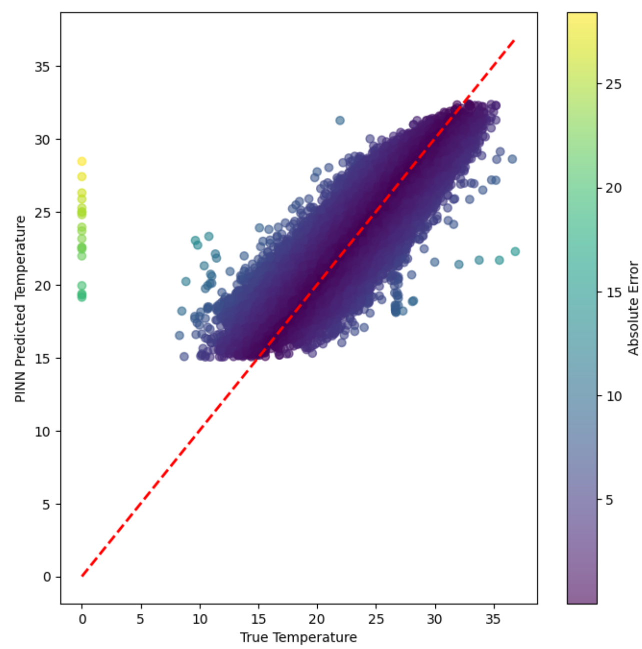

Fig. 2. PINN Predictions vs. True Temperature (Color-coded by Abs Error)

A. Training Behaviour

The physics-informed neural network (PINN) was trained using mini-batch gradient descent with the Adam optimizer. Training and validation losses both decreased steadily, stabilising by epoch 100 at approximately 0.26 in standardized units, with the validation curve closely tracking the training curve. This indicates that the model generalised well and did not over-fit. A physics-loss component, designed to enforce a sinusoidal annual temperature cycle, also declined during training, confirming that the network learned to respect the expected seasonal pattern.

TABLE I: Model Performance Metrics on Test Set

Metric	Test Loss	RMSE (°C)	R^2	MSE (°C^2)	MAE (°C)
Value	0.2579	1.53	0.8659	2.3333	1.1270

B. Predictive Accuracy

On the 20% held-out test set (about 108,768 samples), the PINN achieved a test loss of 0.2579 and produced predictions with the correct shape. Mapping the loss back to temperature units yields an RMSE of roughly 1.53 °C; the variance of the daily temperature data ($\sim$17.4 °C^2) implies a baseline RMSE of about 4.17 °C. Thus, the model reduces the average error by more than half. Detailed metrics calculated on the test data show that the model explains roughly 86% of the variance ($R^2 = 0.8659$) and attains a Mean Squared Error of 2.3333 °C^2, Mean Absolute Error of 1.1270 °C and RMSE of 1.5275 °C. These results indicate that the relatively simple PINN captures the bulk of the daily temperature variability across Bangladesh.

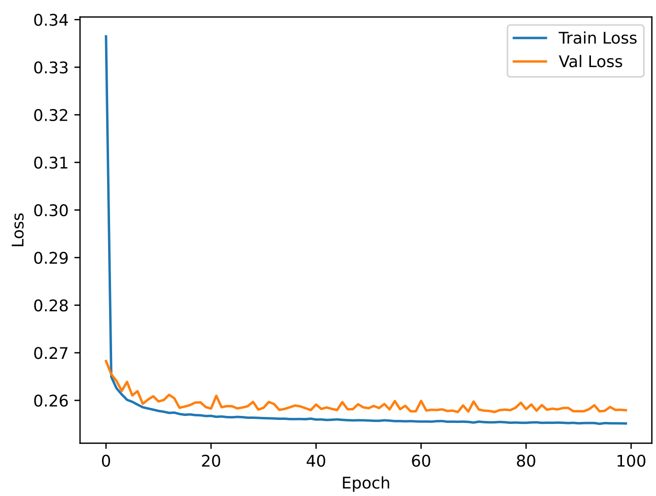

Fig. 3. Training and Validation Loss

C. Analysis

The training–validation loss curves decline together and level off near 0.26, showing that the physics-informed network converges smoothly and generalizes well without over-fitting (Figure 3); this demonstrates that the learning rate and mini-batch optimization are well tuned. A scatter plot of predicted versus actual temperatures confirms that accuracy: nearly all points lie on the 45° line, with only minor dispersion at the extremes, indicating unbiased forecasts across the full temperature range (Figure 2). Complementing these, the feature correlation heatmap reveals only modest correlations between temperature and individual predictors—humidity and rainfall are weakly positive, sunshine slightly negative, and day-of-year moderately positive—underscoring that no single variable explains much variance and that the model must learn complex, seasonally informed relationships 4. Together, these visualizations show that the PINN trains stably, predicts daily temperatures accurately and without bias, and effectively leverages multiple weak signals by adhering to the annual climate cycle.

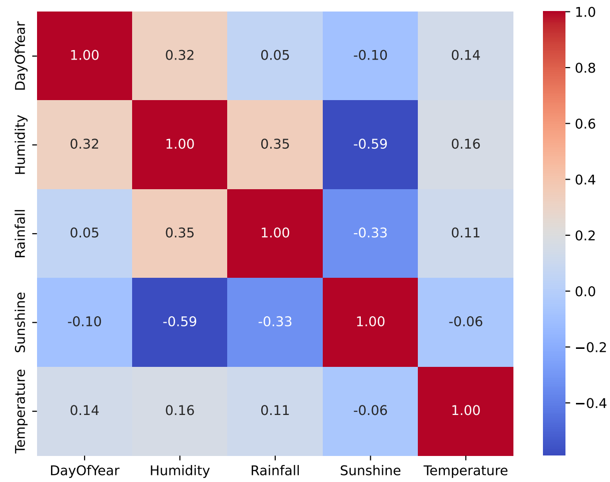

Fig. 4. Feature Correlation Heatmap

V. Discussion

This study demonstrates the use of a Physics-Informed Neural Network (PINN) for daily temperature forecasting in Bangladesh. While the model effectively captures seasonal patterns and improves accuracy, several limitations exist. The relatively simple neural network architecture may not fully capture complex climate dynamics, suggesting that more advanced architectures, such as CNNs or RNNs, could enhance performance. Additionally, the model is trained on data from a limited number of meteorological stations, which may introduce regional biases. Expanding the dataset to include more stations across diverse regions would improve generalizability. The model also focuses solely on daily temperature, and incorporating other variables like humidity or rainfall could further enhance its forecasting ability. Lastly, the model's ability to handle extreme weather events is limited, and refining the loss function or integrating hybrid approaches could better address such anomalies. These improvements would enhance the model's robustness and applicability for long-term climate forecasting and adaptation.

VI. Conclusion

This study demonstrates the efficacy of embedding domain knowledge into data-driven models for climate forecasting. We developed a lightweight physics-informed neural network (PINN) that combines a simple feed-forward architecture with a seasonal prior in the loss function, capturing the annual temperature oscillation characteristic of Bangladesh's monsoon climate. By incorporating this prior and training the network with a stochastic optimization scheme, the model achieves high predictive accuracy and generalizes well across nearly half a million daily observations. The results underscore that even modest neural architectures, when guided by physical insights, can offer substantial improvements over purely statistical approaches.

Beyond accurately predicting daily temperatures, the methodology offers a blueprint for integrating soft physical constraints into machine-learning pipelines more broadly—particularly in data-rich but physics-complex domains like weather forecasting. Future work could explore richer priors (e.g., multiple harmonics or spatial patterns), incorporate additional meteorological variables or station metadata, and experiment with recurrent or attention-based networks to capture temporal dependencies. Extending this framework to jointly predict multiple variables (such as humidity or precipitation) or to estimate uncertainty would further enhance its practical utility. Ultimately, the fusion of physics-guided learning with modern optimization provides a promising avenue for robust, interpretable climate modelling and other applications where data and domain knowledge intersect.

Acknowledgment

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