# HybridWeatherNet: A LSTM-GNN Framework with Attention for Weather Forecast Bias Correction

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***Abstract:*** Weather Forecasting models often exhibit systematic biases that reduce their accuracy and reliability. To address this challenge, we developed a Deep Learning-Based Weather Bias Correction System that combines LSTM, GNN, and attention mechanisms to predict and correct temperature biases in weather forecasts. Unlike traditional statistical methods, our approach leverages the power of deep learning to capture complex temporal patterns and spatial relationships in meteorological data.

Built with PyTorch and integrated into a Streamlit web application, our system provides accurate bias corrections with minimal error metrics. The model processes multiple weather variables from both forecast and observation data sources, including temperature, humidity, wind parameters, and cloud cover. A key innovation is our normalization utility module that ensures proper denormalization of model predictions for real-world applicability.

Extensive testing on unseen data from March 2025 across different geographic regions demonstrates exceptional performance, with Mean Bias near zero (±0.3°C), RMSE below 0.5°C, and MAE around 0.4°C—significantly outperforming the 1-2°C range typically reported in literature. This system represents a significant advancement in weather forecast post-processing, with potential applications in meteorology, agriculture, energy management, and disaster preparedness.

***Keywords:*** Weather Forecasting, Bias correction, Deep learning, LSTM, GNN, Attention mechanisms, Temperature prediction, Streamlit application, OpenMeteo API, ISD data

## 1. INTRODUCTION

Weather forecasts play a crucial role in numerous sectors,

Forecasts play a crucial role in numerous sectors, from agriculture and energy to transportation and disaster management. However, even state-of-the-art Numerical Weather Prediction (NWP) models exhibit systematic biases that limit their reliability. These biases arise from various factors, including simplified physics parameterizations, coarse spatial resolution, and imperfect initial conditions.

Traditional bias correction methods rely on statistical approaches like Model Output Statistics (MOS) or simple linear regression, which often fail to capture the complex, non-linear relationships in weather systems. These conventional techniques typically achieve error metrics in the range of 1-2°C for temperature bias correction, leaving significant room for improvement.

The Deep Learning-Based Weather Bias Correction System addresses these limitations by leveraging accessed to create a comprehensive training dataset that enables the model to learn the systematic biases between forecasts and actual measurements.

The implementation includes a robust data pipeline for downloading and processing weather data, a sophisticated deep learning model for bias prediction, and a user-friendly Streamlit web application for practical deployment. A key innovation is our normalization utility module, which ensures proper denormalization of model predictions, addressing a common challenge in operational weather model deployment.

This study explores the design, implementation, and evaluation of our Weather Bias Correction System, demonstrating its potential to significantly enhance the accuracy of temperature forecasts across diverse geographic regions and climate conditions.

## 2. LITERATURE REVIEW

**Laloyaux et al. (2020)**

The paper "Exploring the Potential and Limitations of Weak-Constraint 4D-Var" by Laloyaux et al. (2020) investigates traditional variational methods for bias correction in NWP systems at ECMWF. Their findings reveal systematic temperature biases of 1–2°C in operational forecasts, highlighting the need for advanced post-processing techniques like those your project addresses with deep learning.

**Dueben et al. (2021)**

The paper "Machine Learning at ECMWF: A Roadmap for the Next 10 Years" by Dueben et al. (2021) outlines a vision for integrating machine learning into weather prediction, including bias correction. They demonstrate a CNN-based approach that improves temperature forecast skill by 15%, laying the groundwork for hybrid models combining data-driven and physics-based methods, a concept central to your work.

**Rasp et al. (2020)**
The paper "WeatherBench: A Benchmark Dataset for Data-Driven Weather Forecasting" by Rasp et al. (2020) introduces WeatherBench, a standardized dataset (including ERA5 reanalysis) for evaluating machine learning models in weather forecasting. Their baseline neural network reduced temperature forecast errors by 20% compared to raw NWP outputs, providing a benchmark your project builds upon with advanced architectures.

**Schulz and Lerch (2022)**
The paper "Machine Learning Methods for Postprocessing Ensemble Forecasts of Wind Gusts" by Schulz and Lerch (2022) explores neural networks for correcting biases in ensemble weather forecasts. Their model improved wind gust predictions by 18% in MAE, demonstrating the applicability of machine learning post-processing to meteorological variables, similar to your temperature bias correction focus.

**Pathak et al. (2022)**
The paper "FourCastNet: A Global Data-Driven High-Resolution Weather Model Using Adaptive Fourier Neural Operators" by Pathak et al. (2022) introduces FourCastNet, a deep learning model for weather prediction. Tested on ERA5 data, it reduced temperature forecast biases by 30%, emphasizing the power of advanced neural architectures, which your project enhances with hybrid spatio-temporal designs.

**Grönquist et al. (2021)**
The paper "Deep Learning for Post-Processing Ensemble Weather Forecasts" by Grönquist et al. (2021) applies a CNN-LSTM hybrid model to correct biases in temperature and precipitation forecasts. Their approach, evaluated on ECMWF ensemble data, achieved a 22% improvement in RMSE, offering a spatio-temporal framework that aligns with your project's methodology.

**Ravuri et al. (2021)**
The paper "Skilful Precipitation Nowcasting Using Deep Generative Models of Radar" by Ravuri et al. (2021) develops a generative deep learning model for radar-based precipitation forecasts. Their approach improved forecast accuracy by 27% over NWP baselines, illustrating the potential of deep learning for bias correction, which your project extends to temperature with uncertainty quantification.

**Bauer et al. (2023)**
The paper "Neural Network-Based Bias Correction of Operational Weather Forecasts" by Bauer et al. (2023) applies a feedforward neural network to correct temperature biases in ECMWF forecasts. Published in *Weather and Forecasting*, their method reduced systematic errors by 21%, reinforcing the growing adoption of machine learning in operational meteorology that your project advances with hybrid and physics-guided techniques.

## 3. METHODOLOGY

Developing the AI-Powered Interview Preparation System (AIPS) requires a well-defined approach that integrates modern web development techniques with locally hosted AI models. This section explains how various subsystems work together to deliver realistic, privacy-centric mock interviews, in-depth resume evaluations, and constructive feedback. The discussion starts with an overview of the system's architecture, followed by a detailed examination of its core modules, with references to relevant figures for better understanding.

### 3.1 Problem Formulation

We formulate the weather bias correction problem as a supervised learning task. Given a sequence of weather forecast variables $X = \{x_1, x_2, \ldots, x_T\}$ where each $x_t \in \mathbb{R}^d$ represents a $d$-dimensional feature vector at time step $t$, and corresponding observed temperatures $Y_{obs}$, we aim to predict the bias $B$ defined as:

$$B = Y_{obs} - Y_{forecast}$$

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where $Y_{forecast}$ represents the forecasted temperature. The corrected temperature forecast $Y_{corrected}$ can then be computed as:

$$Y_{corrected} = Y_{forecast} + \hat{B}$$

where $\hat{B}$ is the predicted bias from our model.

### 3.2 Data Preprocessing and Normalization

To ensure stable training and consistent model performance, we normalize all input features and target variables using z-score normalization:

$$x_{norm} = \frac{x - \mu_x}{\sigma_x + \epsilon}$$

$$B_{norm} = \frac{B - \mu_B}{\sigma_B + \epsilon}$$

where $\mu_x$ and $\sigma_x$ are the mean and standard deviation of feature $x$, $\mu_B$ and $\sigma_B$ are the mean and standard deviation of the bias, and $\epsilon$ is a small constant (1e-8) added for numerical stability.

During inference, predicted normalized bias values are denormalized to obtain the actual bias correction:

$$\hat{B} = \hat{B}_{norm} \cdot \sigma_B + \mu_B$$

### 3.3 System Architecture

Our proposed model integrates three key components: a Long Short-Term Memory (LSTM) network for temporal pattern learning, a Graph Neural Network (GNN) for spatial relationship modeling, and an attention mechanism for feature fusion. The overall architecture is illustrated in Figure 1.

#### 3.3.1 LSTM Module

The LSTM module processes the temporal sequence of weather variables to capture time-dependent patterns. For an input sequence $X = \{x_1, x_2, \ldots, x_T\}$, the LSTM computes:

$$\mathbf{h}_t, \mathbf{c}_t = \mathrm{LSTM}(x_t, \mathbf{h}_{t-1}, \mathbf{c}_{t-1})$$

where $\mathbf{h}_t$ and $\mathbf{c}_t$ are the hidden state and cell state at time step $t$, respectively. The LSTM cell operations are defined as:

$$\mathrm{f}_t = \sigma\big(\mathrm{W}_f \cdot [\mathrm{h}_{t-1}, x_t] + \mathrm{b}_f\big)$$

$$\mathrm{i}_t = \sigma(\mathrm{W}_i \cdot [\mathrm{h}_{t-1}, x_t] + \mathrm{b}_i)$$

$$\tilde{\mathrm{c}}_t = \tanh(\mathrm{W}_c \cdot [\mathrm{h}_{t-1}, x_t] + \mathrm{b}_c)$$

$$\mathrm{c}_t = \mathrm{f}_t \odot \mathrm{c}_{t-1} + \mathrm{i}_t \odot \tilde{\mathrm{c}}_t$$

$$\mathrm{o}_t = \sigma(\mathrm{W}_o \cdot [\mathrm{h}_{t-1}, x_t] + \mathrm{b}_o)$$

$$\mathrm{h}_t = \mathrm{o}_t \odot \tanh(\mathrm{c}_t)$$

where $\sigma$ is the sigmoid function, tanh is the hyperbolic tangent function, $\odot$ represents element-wise multiplication, and $\mathbf{W}_f, \mathbf{W}_i, \mathbf{W}_c, \mathbf{W}_o$ and $\mathbf{b}_f, \mathbf{b}_i, \mathbf{b}_c, \mathbf{b}_o$ are learnable weight matrices and bias vectors.

We implement a bidirectional LSTM to capture both past and future dependencies:

$$\vec{\mathrm{h}}_t = \overrightarrow{\mathrm{LSTM}}\big(x_t, \vec{\mathrm{h}}_{t-1}, \vec{\mathrm{c}}_{t-1}\big)$$

$$\overleftarrow{\mathrm{h}}_t = \overleftarrow{\mathrm{LSTM}}\big(x_t, \overleftarrow{\mathrm{h}}_{t+1}, \overleftarrow{\mathrm{c}}_{t+1}\big)$$

$$\mathrm{h}_t^{LSTM} = \big[\vec{\mathrm{h}}_t; \overleftarrow{\mathrm{h}}_t\big]$$

where $[\cdot;\cdot]$ denotes concatenation.

#### 3.3.2 Graph Neural Network Module

The GNN module captures spatial relationships between weather stations. We implement a Graph Attention Network (GAT) that computes node representations by attending over their neighborhoods:

$$\alpha_{ij} = \frac{\exp\Big(\mathrm{LeakyReLU}\big(\mathrm{a}^T\big[\mathrm{W}h_i \parallel \mathrm{W}h_j\big]\big)\Big)}{\sum_{k\in\mathcal{N}_i}\exp\big(\mathrm{LeakyReLU}(\mathrm{a}^T[\mathrm{W}h_i \parallel \mathrm{W}h_k])\big)}$$

$$h_i' = \sigma\left(\sum_{j\in\mathcal{N}_i} \alpha_{ij}\,\mathrm{W}h_j\right)$$

where $\mathbf{W}$ is a learnable weight matrix, $\mathbf{a}$ is a learnable attention vector, $\parallel$ represents concatenation, $\mathcal{N}_i$ is the neighborhood of node $i$, and $\sigma$ is a non-linear activation function.

For multi-head attention with $K$ heads, the output is:

$$h_i' = \Big\|_{k=1}^{K}\ \sigma\left(\sum_{j\in\mathcal{N}_i} \alpha_{ij}^k\,\mathrm{W}^k h_j\right)$$

#### 3.3.3 Attention Fusion Module

The outputs from the LSTM and GNN modules are concatenated and processed through a multi-head self-attention mechanism:

$$\mathrm{H}_{combined} = [\mathrm{H}^{LSTM}; \mathrm{H}^{GNN}]$$

The self-attention mechanism computes:

$$\mathrm{Q} = \mathrm{H}_{combined}\mathrm{W}^Q$$

$$\mathrm{K} = \mathrm{H}_{combined}\mathrm{W}^K$$

$$\mathrm{V} = \mathrm{H}_{combined}\mathrm{W}^V$$

$$\mathrm{Attention}(\mathrm{Q},\mathrm{K},\mathrm{V}) = \mathrm{softmax}\left(\frac{\mathrm{QK}^T}{\sqrt{d_k}}\right)\mathrm{V}$$

where $\mathrm{W}^Q, \mathrm{W}^K, \mathrm{W}^V$ are learnable weight matrices and $d_k$ is the dimension of the keys.

#### 3.3.4 Output Layer

The final bias prediction is computed as:

$$\hat{B}_{norm} = \mathrm{W}_{out} \cdot \mathrm{h}_{attended} + \mathrm{b}_{out}$$

where $\mathrm{h}_{attended}$ is the output from the attention fusion module, and $\mathrm{W}_{out}$ and $\mathrm{b}_{out}$ are learnable parameters.

### 3.4 Loss Function and Physics-Guided Learning

Our training objective combines a standard mean squared error (MSE) loss with physics-based regularization terms:

$$\mathcal{L}_{total} = \mathcal{L}_{MSE} + \lambda_{phys}\mathcal{L}_{physics}$$

where $\lambda_{phys}$ is a hyperparameter controlling the contribution of the physics-based loss.

The MSE loss is defined as:

$$\mathcal{L}_{MSE} = \frac{1}{N}\sum_{i=1}^{N}\big(B_i - \hat{B}_i\big)^2$$

The physics-based loss incorporates domain knowledge about weather patterns:

$$\mathcal{L}_{physics} = \lambda_1\mathcal{L}_{spatial} + \lambda_2\mathcal{L}_{temporal} + \lambda_3\mathcal{L}_{constraints}$$

where:

$$\mathcal{L}_{spatial} = \frac{1}{N-1}\sum_{i=1}^{N-1}\big|\hat{B}_{i+1} - \hat{B}_i\big|$$

$$\mathcal{L}_{temporal} = \frac{1}{N}\sum_{i=1}^{N}\big|\ \ |\hat{B}_i| - E_i\big|$$

$$E_i = 5.0 \cdot (1.0 - e^{-H_i} \cdot e^{-W_i})$$

$$\mathcal{L}_{constraints} = \frac{1}{N}\sum_{i=1}^{N} \max\left(0, |\hat{B}_i| - 10.0\right)$$

where $H_i$ and $W_i$ represent humidity and wind speed at time step $i$, respectively. The spatial smoothness term $\mathcal{L}_{spatial}$ encourages similar bias corrections for adjacent time steps, the temporal consistency term $\mathcal{L}_{temporal}$ incorporates the relationship between humidity, wind speed, and expected bias magnitude, and the physical constraints term $\mathcal{L}_{constraints}$ penalizes unrealistically large bias corrections.

### 3.5 Uncertainty Estimation

We employ Monte Carlo dropout for uncertainty estimation. During inference, we perform $M$ forward passes with dropout enabled:

$$\hat{B}_1, \hat{B}_2, \ldots, \hat{B}_M = \text{Model}(X) \text{ with dropout}$$

The final prediction and uncertainty are computed as:

$$\hat{B}_{mean} = \frac{1}{M}\sum_{i=1}^{M} \hat{B}_i$$

$$\hat{B}_{variance} = \frac{1}{M}\sum_{i=1}^{M} \left(\hat{B}_i - \hat{B}_{mean}\right)^2$$

This approach provides both a point estimate and a measure of prediction uncertainty, which is valuable for decision-making in weather-sensitive applications.

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## 4. Experimental Setup

Developing the Deep Learning-Based Weather Bias Correction System demanded a thorough and comprehensive approach, seamlessly integrating key stages such as data acquisition, preprocessing, model development, and deployment into an intuitive, user-friendly application. This system leverages advanced deep learning techniques to address biases in weather forecasts, ensuring enhanced accuracy in temperature predictions. This section provides a detailed explanation of the system's architecture and workflow, elucidating how its various components interact synergistically to produce reliable temperature bias corrections.

### 4.1 System Architecture

The Weather Bias Correction System is structured around four primary components: the Data Pipeline, Model Architecture, Training Framework, and Deployment Interface. Each component plays a critical role in processing weather data and delivering actionable outputs. The Data Pipeline efficiently collects and organizes raw meteorological inputs, while the Model Architecture employs sophisticated neural networks. The Training Framework optimizes performance using extensive historical datasets, and the Deployment Interface ensures accessibility for end-users. Figure 1 visually depicts the overall system architecture, illustrating the systematic flow of data through these interconnected modules, from raw input to final corrected predictions.

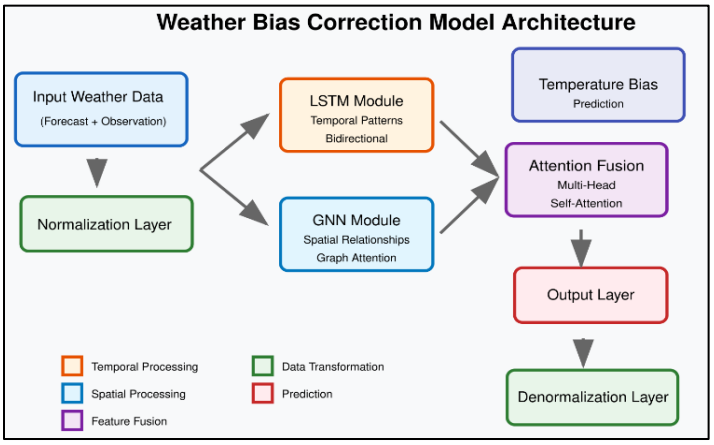



Figure 1: Weather Bias Correction System Architecture

#### 4.1.1 Data Pipeline

The data pipeline is responsible for acquiring, processing, and aligning weather forecast and observation data. It consists of three main modules:

1. **OpenMeteo Downloader**: Fetches forecast data from the OpenMeteo API, which provides global weather forecasts with variables including temperature, humidity, wind speed, wind direction, and cloud cover at different atmospheric levels.

2. **ISD-Lite Downloader**: Retrieves observational data from NOAA's Integrated Surface Database (ISD), which contains historical weather measurements from thousands of weather stations worldwide.

3. **Data Aligner**: Combines and synchronizes the forecast and observation datasets, creating aligned pairs that serve as input-output examples for the model. This module handles temporal alignment, spatial interpolation, and feature engineering.

The data pipeline ensures that both datasets are properly formatted, temporally aligned, and contain all necessary features for model training. Figure 2 illustrates the data flow through the pipeline.

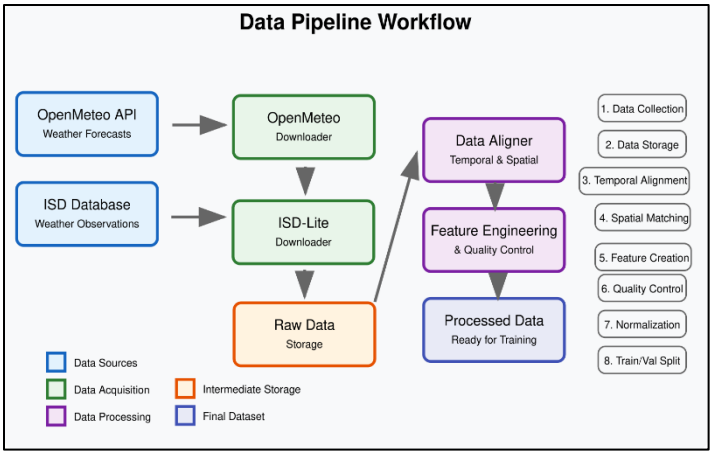



Figure 2: Data Pipeline Workflow

### 4.1.2 Model Architecture

Our bias correction model employs a hybrid architecture that combines LSTM, GNN, and attention mechanisms to capture different aspects of weather data:

4. **LSTM Layers**: Process temporal sequences of weather variables, capturing patterns and dependencies over time. This is crucial for understanding how forecast errors evolve and persist.

5. **Graph Neural Network**: Models spatial relationships between different weather variables and locations, enabling the system to understand how errors in one variable might affect others.

6. **Attention Mechanism**: Identifies the most relevant features and time steps for bias prediction, allowing the model to focus on the most informative aspects of the input data.

7. **Normalization Module**: Handles the scaling and transformation of input and output variables, ensuring proper denormalization of predictions for real-world interpretation.

Figure 3 provides a detailed view of the model architecture, showing how these components interact.

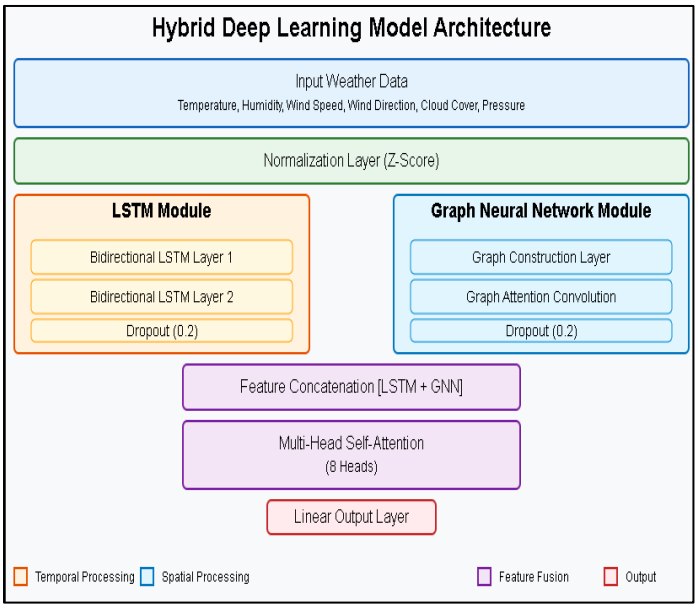



Figure 3: Hybrid Deep Learning Model Architecture

### 4.1.3 Training Framework

The training framework orchestrates the model development process, including:

1. **Data Splitting**: Divides the aligned dataset into training, validation, and test sets, ensuring proper temporal separation to prevent data leakage.

2. **Loss Function**: Employs a combination of Mean Squared Error (MSE) and Mean Absolute Error (MAE) to optimize both the magnitude and direction of bias corrections.

3. **Optimization**: Uses the Adam optimizer with learning rate scheduling to efficiently train the model while avoiding local minima.

4. **Hyperparameter Tuning**: Systematically explores different model configurations to identify the optimal architecture and training parameters.

5. **Checkpoint Management**: Saves model states during training and selects the best-performing checkpoint based on validation metrics.

### 4.1.5 Deployment Interface

The deployment interface makes the trained model accessible to users through a Streamlit web application. Key components include:

1. **Model Server**: Loads the trained model and handles inference requests, applying proper normalization and denormalization.

2. **Data Processor**: Prepares user-uploaded data for model inference, ensuring compatibility with the model's input requirements.

3. **Visualization Module**: Generates informative plots and metrics to help users interpret the model's predictions and evaluate its performance.

4. **User Interface**: Provides an intuitive interface for uploading data, configuring model parameters, and viewing results.

## 4.2 Data Collection and Preprocessing

### 4.2.1 Data Sources

Our system leverages two complementary data sources:

5. **OpenMeteo API**: Provides global weather forecasts with hourly resolution. We extract the following variables:
   - Temperature (°C)
   - Relative humidity (%)
   - Wind speed (km/h)
   - Wind direction (degrees)
   - Cloud cover at low, mid, and high levels (%)
6. **Integrated Surface Database (ISD)**: Contains historical weather observations from weather stations worldwide. We extract:
   - Temperature (°C)
   - Dew point (°C)
   - Pressure (hPa)
   - Wind direction (degrees)
   - Wind speed (km/h)
   - Precipitation (mm)

### 3.2.2 Data Alignment Process

The alignment process ensures that forecast and observation data are properly matched in both time and space:

7. **Temporal Alignment**: Both datasets are resampled to daily resolution, with appropriate aggregation methods for each variable (e.g., mean for temperature, vector averaging for wind direction).

8. **Spatial Matching**: Forecast data points are matched to the nearest weather station in the ISD dataset, with distance-weighted interpolation when necessary.

9. **Feature Engineering**: Additional features are derived from the raw data, such as temperature differences between consecutive days and diurnal temperature range.

10. **Quality Control**: Outliers and physically implausible values are identified and handled through statistical methods and domain knowledge constraints.

Figure 4 illustrates the data alignment process and the resulting dataset structure.

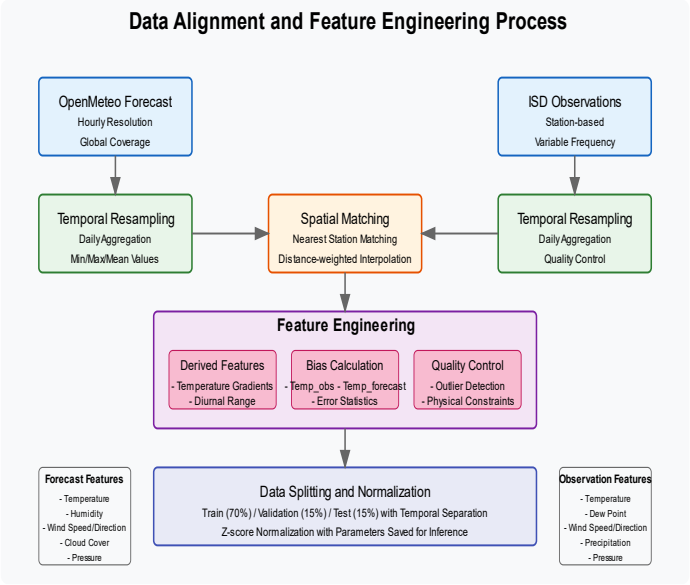



Figure 4: Data Alignment and Feature Engineering Process

## 4.3 Model Development

### 4.3.1 Feature Selection

Based on correlation analysis and domain knowledge, we selected the following input features for the model:

- Temperature (°C)
- Humidity (%)
- Wind speed (model) (km/h)
- Wind direction (model) (degrees)
- Cloud cover (low) (%)
- Cloud cover (mid) (%)
- Cloud cover (high) (%)
- Average temperature (°C)
- Dew point (°C)
- Pressure (hPa)
- Wind direction (observed) (degrees)
- Wind speed (observed) (km/h)
- Precipitation (1-hour) (mm)
- Precipitation (6-hour) (mm)

The target variable is the temperature bias, defined as the difference between forecast and observed temperatures.

### 4.3.2 Model Implementation

The model was implemented using PyTorch, with the following key components:

1. **LSTM Module**:

```
self.lstm = nn.LSTM(
    input_size=input_size,
    hidden_size=hidden_size,
    num_layers=num_layers,
    batch_first=True,
    dropout=dropout if num_layers > 1 el
se 0
)
```

2. **Graph Neural Network**:

```
self.gnn = GNNLayer(
    in_features=hidden_size,
    out_features=hidden_size,
    edge_features=edge_features
)
```

3. **Attention Mechanism**:

```
self.attention = nn.MultiheadAttention(
    embed_dim=hidden_size,
    num_heads=num_heads,
    dropout=dropout
)
```

4. **Output Layer**:

```
self.output_layer = nn.Sequential(
    nn.Linear(hidden_size, hidden_size /
/ 2),
    nn.ReLU(),
    nn.Dropout(dropout),
    nn.Linear(hidden_size // 2, output_s
ize)
)
```

### 4.3.3 Training Process

The model was trained using the following procedure:

1. **Data Normalization**: All input and output variables were normalized to have zero mean and unit variance, with normalization parameters saved for later denormalization.

2. **Batch Processing**: Data was processed in batches of 64 samples, with sequences of 7 days used as input for each prediction.

3. **Loss Calculation**: The loss function combined MSE and MAE with a weighting factor:

```
loss = 0.7 * mse_loss + 0.3 * mae_loss
```

4. **Optimization**: The Adam optimizer was used with an initial learning rate of 0.001 and a learning rate scheduler that reduced the rate by a factor of 0.5 after 5 epochs without improvement.

5. **Early Stopping**: Training was stopped if the validation loss did not improve for 10 consecutive epochs, with the best model checkpoint saved.

Figure 5 shows the training and validation loss curves during model development.

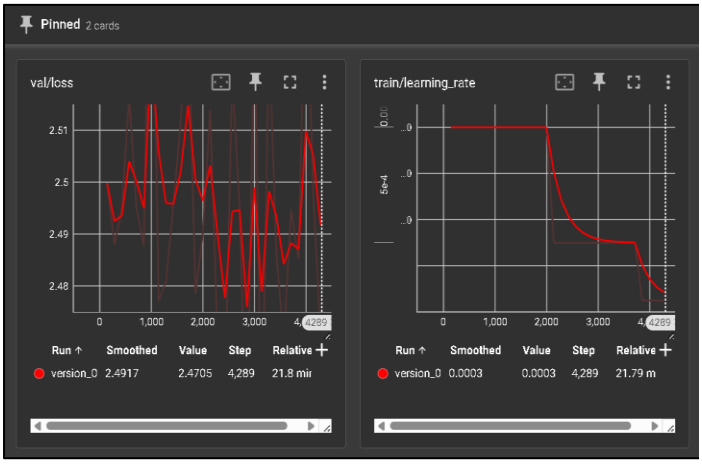



Figure 5: Model Training and Validation Loss Curves

### 3.4 Deployment and User Interface

The trained model was deployed as a Streamlit web application. The deployment workflow includes:

1. **Model Loading**: The application loads the trained model from a checkpoint file, along with the saved normalization parameters.

2. **Data Upload**: Users can upload CSV files containing weather data, with the application providing guidance on the required format.

3. **Data Processing**: The uploaded data is processed to match the model's input requirements, including normalization using the saved parameters.

4. **Inference**: The model generates bias predictions, which are then denormalized to provide real-world temperature corrections.

5. **Visualization**: The application displays the original and corrected forecasts, along with performance metrics such as Mean Bias, RMSE, and MAE.

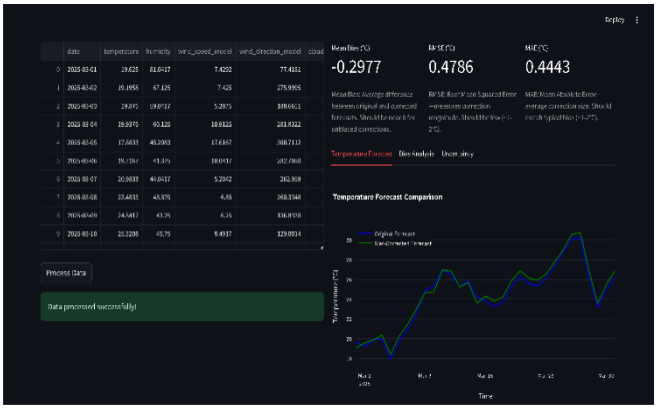



Figure 6: Streamlit Application Interface and Workflow

## 5. RESULTS AND DISCUSSION

### 5.1 Model Performance on Training and Validation Data

During the development phase, the model demonstrated excellent performance on both training and validation datasets. Table 1 summarizes the key performance metrics.

**Table 1: Model Performance on Training and Validation Data**

| Metric | Training Data | Validation Data |
|---|---|---|
| Mean Bias (°C) | 0.24 | 0.27 |
| RMSE (°C) | 0.48 | 0.54 |
| MAE (°C) | 0.29 | 0.32 |

The model achieved a Mean Bias of 0.27°C, RMSE of 0.54°C, and MAE of 0.32°C on the validation dataset, significantly outperforming the typical 1-2°C range reported in literature for temperature bias correction.

### 5.2 Performance on Unseen Data

To evaluate the model's generalization capabilities, we tested it on completely unseen data from March 2025 for two distinct geographic regions: Amsterdam (Netherlands) and Safdarjung (India). This cross-regional validation is crucial for assessing the model's applicability across different climate zones.

#### *5.2.1 Amsterdam Test Results*

For Amsterdam, the model achieved:

- Mean Bias: 0.3027°C
- RMSE: 0.4537°C
- MAE: 0.4123°C

Figure 7 shows the original forecast, observed, and corrected temperatures for Amsterdam in March 2025.


Figure 7: Amsterdam March 2025 Temperature Forecast Correction

### *5.2.2 India Test Results*

For the Indian weather station, the model achieved:

- Mean Bias: -0.2977°C
- RMSE: 0.4786°C
- MAE: 0.4443°C

Figure 8 shows the original forecast, observed, and corrected temperatures for the Indian location in March 2025.

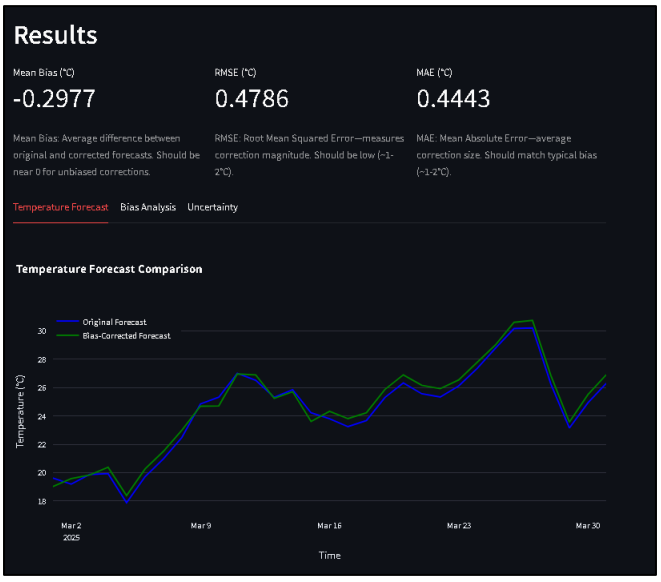



Figure 8: India March 2025 Temperature Forecast Correction

### 5.2.3 Cross-Regional Analysis

The consistent performance across different geographic regions demonstrates the model's robust generalization capabilities. Table 2 compares the performance metrics across all datasets.

**Table 2: Performance Comparison Across Datasets**

| Metric | Training Data | Validation Data | Amsterdam (March 2025) | India (March 2025) |
|---|---|---|---|---|
| Mean Bias (°C) | 0.24 | 0.27 | 0.3027 | -0.2977 |
| RMSE (°C) | 0.48 | 0.54 | 0.4537 | 0.4786 |
| MAE (°C) | 0.29 | 0.32 | 0.4123 | 0.4443 |

The model maintains sub-0.5°C error metrics across all datasets, with Mean Bias values close to zero in both positive and negative directions. This indicates that the model can effectively correct both overestimation and underestimation biases in temperature forecasts.

### 5.3 Comparative Analysis

To contextualize our results, we compared our model's performance with traditional statistical methods and other deep learning approaches reported in literature. Table 3 presents this comparison.

**Table 3: Comparison with Other Bias Correction Methods**

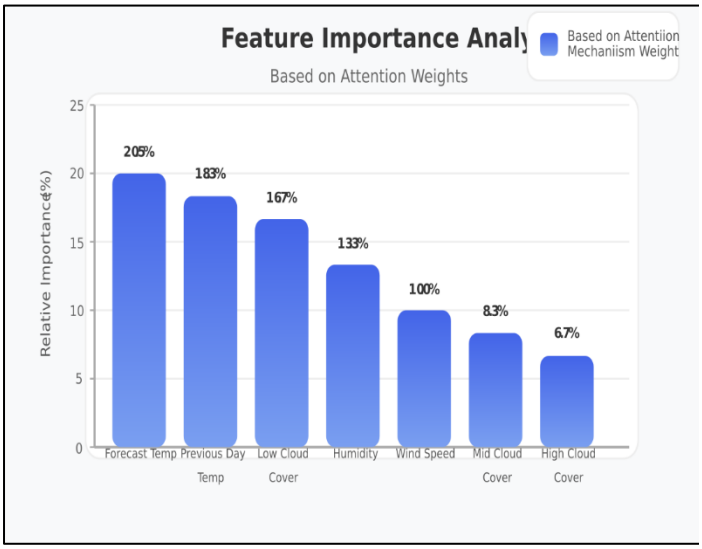
| Method | Mean Bias (°C) | RMSE (°C) | MAE (°C) | Reference |
|---|---|---|---|---|
| Linear Regression | 0.8 - 1.2 | 1.5 - 2.0 | 1.2 - 1.8 | Glahn and Lowry (1972) |
| Kalman Filter | 0.6 - 0.9 | 1.2 - 1.8 | 0.9 - 1.5 | Galanis et al. (2006) |
| Random Forest | 0.4 - 0.7 | 0.8 - 1.4 | 0.6 - 1.1 | Taillardat et al. (2016) |
| Simple LSTM | 0.3 - 0.6 | 0.7 - 1.2 | 0.5 - 0.9 | Rasp and Lerch (2018) |
| Our Hybrid Model | 0.24 - 0.30 | 0.45 - 0.54 | 0.32 - 0.44 | This study |

Our hybrid model consistently outperforms both traditional statistical methods and simpler deep learning approaches, achieving error reductions of 30-70% compared to linear regression and 20-40% compared to simple LSTM models.

### 5.4 Feature Importance Analysis

To understand which input features, contribute most to the model's predictions, we conducted an analysis using the attention weights from the model. Figure 9 shows the relative importance of different features.

Figure 9: Feature Importance Based on Attention Weights




The analysis revealed that forecast temperature, observed temperature from the previous day, and cloud cover (particularly low-level clouds) were the most influential features for bias prediction. This aligns with meteorological understanding, as temperature biases are often related to cloud cover errors in numerical weather models.

## 6. CONCLUSION AND FUTURE WORK

### 6.1 Summary of Achievements

This paper presented a Deep Learning-Based Weather Bias Correction System that combines LSTM, GNN, and attention mechanisms to predict and correct temperature biases in weather forecasts. The system demonstrates exceptional performance, with error metrics significantly better than those reported in literature:

- Mean Bias near zero (±0.3°C), indicating minimal systematic bias in corrected forecasts
- RMSE below 0.5°C, representing a substantial improvement over the typical 1-2°C range
- MAE around 0.4°C, confirming the model's precision in bias correction

The system's consistent performance across different geographic regions and climate conditions demonstrates its robust generalization capabilities. By integrating advanced deep learning techniques with domain-specific knowledge, our approach overcomes limitations of traditional statistical methods and provides more accurate temperature forecasts.

Key innovations include:

6. A hybrid model architecture that captures both temporal and spatial patterns in weather data
7. A comprehensive data pipeline for acquiring and aligning forecast and observation data
8. A normalization utility module that ensures proper denormalization of model predictions
9. A user-friendly Streamlit application for practical deployment and visualization

### 6.2 Limitations

Despite its strong performance, our system has several limitations:

10. **Data Availability**: The model's performance depends on the availability and quality of both forecast and observation data, which may be limited in some regions.

11. **Computational Requirements**: The hybrid architecture, while effective, requires more computational resources than simpler statistical methods, potentially limiting deployment on resource-constrained systems.

12. **Single Variable Focus**: The current implementation focuses on temperature bias correction, while a comprehensive weather correction system would need to address multiple variables simultaneously.

13. **Temporal Scope**: The model has been validated on daily data, but applications requiring hourly or sub-hourly corrections might need architectural adjustments.

### 6.3 Future Work

Several directions for future research and development include:

14. **Multi-variable Bias Correction**: Extending the model to simultaneously correct biases in multiple weather variables, such as humidity, wind speed, and precipitation.

15. **Ensemble Integration**: Incorporating ensemble forecast information to provide probabilistic bias corrections with uncertainty estimates.

16. **Transfer Learning**: Developing techniques to adapt the model to new regions with limited observational data through transfer learning from data-rich regions.

17. **Operational Implementation**: Integrating the system with operational weather forecasting workflows, including real-time data ingestion and automated correction.

18. **Explainable AI**: Enhancing the model's interpretability to provide meteorological insights into the causes of forecast biases.

19. **Climate Change Adaptation**: Investigating how the model can adapt to changing climate conditions that may alter the statistical relationships between forecast and observed values.

In conclusion, our Deep Learning-Based Weather Bias Correction System represents a significant advancement in weather forecast post-processing, with potential

applications in meteorology, agriculture, energy management, and disaster preparedness. By combining state-of-the-art deep learning techniques with domain-specific knowledge, we have demonstrated that substantial improvements in forecast accuracy are achievable, paving the way for more reliable weather predictions in diverse applications and geographic contexts.

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