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ARTICLE

Storm Whisperers: Predicting Thunderstorms with Long Short-Term Heuristic Memory Model

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ABSTRACT: Accurate thunderstorm prediction is essential for safeguarding public safety and optimizing resource management, particularly in increasingly unpredictable weather patterns. This study explores the use of Long Short-Term Memory (LSTM) neural networks enhanced with heuristic mechanisms as a cutting-edge method for predicting thunderstorm events. By leveraging the inherent ability of LSTMs to capture long-range temporal dependencies, the proposed heuristic-based LSTM (LSTHM) model systematically analyzes historical meteorological data to discern critical patterns indicative of thunderstorm formation. The LSTHM framework enhances the model's robustness in diverse climatic conditions through its heuristic mechanisms. The network is trained using a comprehensive dataset, encompassing varied weather scenarios to ensure generalizability and accuracy. Performance evaluation against traditional forecasting methodologies reveals that the LSTHM model consistently demonstrates superior predictive accuracy and reliability in estimating the onset and intensity of thunderstorms. The results substantiate the efficacy of the proposed approach, highlighting its potential to improve forecasting precision and elucidate the complex dynamics underlying storm development. This research significantly contributes to meteorological prediction, showcasing the applicability of machine learning and deep learning techniques in advancing weather forecasting models. Ultimately, the insights derived from this study aim to enhance timely decision-making processes during weather-related emergencies, thereby mitigating the impacts of severe thunderstorms on vulnerable communities.

KEYWORDS: Meteorological Parameters; Machine Learning; Deep Learning; Weather; Prediction; Thunderstorm.

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1 Introduction

Thunderstorms are among the most dynamic and destructive weather phenomena, posing significant risks to life, property, and critical infrastructure [1].The intensification of extreme weather events, exacerbated by climate change, has amplified the urgency for precise and timely forecasting [2]. Although traditional meteorological models form the foundation of weather prediction, they often struggle to effectively capture the complex, non-linear interactions between atmospheric variables, particularly during fast-evolving convective events such as thunderstorms [3].

In recent years, machine learning (ML), especially deep learning models like Long Short-Term Memory (LSTM) networks, has been increasingly applied in the field of weather forecasting. These models excel in handling temporal data and capturing long-range dependencies, making them suitable for modeling meteorological time-series data [4–6]. Furthermore, Transformer-based models have emerged as powerful alternatives for sequence modeling, offering advantages in handling longer sequences and parallel computation. However, while these architectures have shown promise, their application has often focused on broader or more generalized weather prediction tasks—such as temperature or precipitation forecasting over extended periods or regions—rather than on short-term, high-impact events like thunderstorms.

Despite the growing body of ML-based weather prediction research [5–9], a critical gap remains in models specifically tailored to the unique spatiotemporal dynamics of thunderstorm development. Many existing studies [3,10,11] do not comprehensively integrate localized meteorological features or lack interpretability and real-time applicability, which are crucial for operational deployment. This study aims to address these shortcomings by designing an LSTM-based framework specifically optimized for thunderstorm forecasting, grounded in fine-grained, high-resolution weather data.

By focusing on key atmospheric parameters such as temperature, humidity, wind speed, and pressure, our model seeks to uncover and exploit patterns that precede thunderstorm onset. In doing so, we contribute a specialized approach that improves the precision of forecasting and offers practical utility for early warning systems, emergency planning, and climate resilience efforts.

1.1 Motivation

The design of “Storm Whisperers: Predicting Thunderstorms with Long Short-Term Memory Neural Network" is driven by a growing need for specialized, high-resolution forecasting tools in an era of climate instability. Thunderstorms, with their sudden onset and localized impact, remain among the most difficult extreme weather events to predict with sufficient lead time [1]. Although machine learning, particularly LSTM and Transformer architectures, has gained traction in meteorological research, much of the existing work prioritizes generalized forecasting objectives, often overlooking the nuanced requirements of short-term, high-impact storm prediction [3,12].

Our motivation stems from the recognition that a targeted approach, explicitly focused on thunderstorm dynamics, is both timely and necessary. Unlike broader forecasting tasks, forecasting thunderstorms requires an acute sensitivity to rapid atmospheric changes and localized data trends. By training LSTM networks on historical weather datasets that emphasize these conditions, our study aims to build a model that not only improves predictive accuracy but also functions effectively under real-time constraints.

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Furthermore, our work is guided by the broader societal need for improved preparedness and response to weather hazards. As climate change continues to increase the frequency and unpredictability of extreme weather events, the importance of data-driven adaptive forecasting models cannot be overstated [13,14]. Therefore, by integrating deep learning (DL) techniques [15] into operational meteorology, we strive to bridge the gap between scientific innovation and public safety, enabling more informed decision making during severe weather events.

Ultimately, this study contributes to the evolving landscape of meteorological research by proposing a model that is both technically robust and application-oriented, tailored specifically to the complex challenge of thunderstorm prediction.

1.2 Research Gap & Challenges

1.2.1 Research Gap

1. **Integration of Deep Learning in Meteorology:** While traditional meteorological models [3,12] have been extensively studied, there remains a significant gap in applying advanced deep learning techniques, particularly LSTM networks, for thunderstorm prediction. Most existing research focuses on simpler machine learning algorithms, which may not adequately capture the complexities of atmospheric dynamics [16].
2. **Limited Historical Data Utilization:** Many studies [17,18] rely on smaller datasets or fail to utilize the rich, high-frequency meteorological data available today fully. The challenge lies in effectively harnessing this data to train LSTM models capable of generalizing well across various weather conditions and geographical regions.
3. **Real-Time Prediction Capabilities:** Current forecasting systems [19,20] often struggle with real-time predictions due to the time-consuming nature of data processing and model training. There is a need for research that emphasizes the development of efficient LSTM architectures that can deliver timely insights for impending thunderstorms.
4. **Understanding Model Interpretability:** As deep learning models, including LSTMs, often operate as *black boxes*, understanding the underlying decision-making processes remains challenging [21]. This gap in interpretability can hinder trust and adoption in operational settings.

1.2.2 Challenges

1. **Data Quality and Availability:** High-quality, consistent, and comprehensive meteorological data is crucial for training effective LSTM models. However, missing data, variations in data collection methods, and the need for extensive preprocessing can complicate model development.
2. **Complex Atmospheric Interactions:** Thunderstorms arise from many interacting atmospheric variables. Capturing these complex relationships within an LSTM framework requires careful feature selection and engineering, which can be challenging and time-consuming.
3. **Computational Resources:** Training DL models, especially on large datasets, demands significant computational power and resources. Ensuring that the model can be efficiently trained and deployed in real-time settings is a practical challenge.
4. **Validation and Benchmarking:** Establishing robust validation techniques and benchmarks to compare LSTM performance against traditional forecasting methods is essential for

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demonstrating efficacy. This requires careful consideration of evaluation metrics that accurately reflect predictive accuracy in meteorological contexts.

By addressing these research gaps and challenges, *Storm Whisperers* aims to contribute valuable insights to thunderstorm prediction, paving the way for more reliable and effective forecasting systems.

1.3 Contribution

1. **Innovative Heuristic-Enhanced Methodology:** The proposed LSTHM model represents a significant advancement in meteorological forecasting by combining the temporal modeling strength of LSTMs with adaptive heuristic mechanisms. This novel approach bridges the gap between conventional forecasting techniques and advanced machine learning methods, paving the way for more accurate and adaptable thunderstorm predictions.
2. **Dynamic and Adaptive Learning Framework:** By integrating heuristic optimization within the LSTM architecture, the model dynamically adjusts its learning process based on evolving atmospheric conditions. This adaptive capability ensures the model remains responsive to sudden changes in weather patterns, enhancing real-time prediction accuracy.
3. **Comprehensive and Multivariate Data Utilization:** The study leverages diverse historical meteorological data. The model learns complex interactions between meteorological factors by analyzing these multidimensional data streams, significantly improving predictive performance.
4. **Real-Time Prediction and Decision Support:** The LSTHM framework focuses on real-time thunderstorm forecasting, addressing the critical need for rapid and accurate predictions in emergency management. This capability supports timely decision-making and community safety, mitigating the risks associated with severe weather events.
5. **Enhanced Interpretability and Model Transparency:** The integration of heuristic mechanisms not only improves prediction accuracy but also enhances model interpretability. By providing insights into how meteorological factors contribute to thunderstorm development, the model aids meteorologists and decision-makers in understanding the prediction process.
6. **Insights into Thunderstorm Dynamics:** Besides forecasting accuracy, the model aims to better understand thunderstorm dynamics by examining the temporal and spatial interactions among atmospheric variables. This contribution is crucial for advancing knowledge in meteorology and improving long-term forecasting models.
7. **Community Safety and Resilience:** This research aims to enhance public safety through more accurate and timely thunderstorm predictions. The LSTHM model contributes to community resilience and preparedness in extreme weather events by reducing forecast errors and enabling proactive responses.

Through these contributions, the proposed *Storm Whisperers* model aims to impact meteorology meaningfully, advancing theoretical knowledge and practical applications in thunderstorm prediction.

2 Literature Survey

In recent years, the application of ML in meteorology has gained traction, particularly with the rise of DL techniques. This literature survey highlights key studies and advancements relevant to

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using LSTM networks for thunderstorm prediction and the broader context within meteorological forecasting.

2.1 Traditional Meteorological Models

Traditional forecasting methods, such as numerical weather prediction (NWP), have been the cornerstone of meteorological science [22,23]. These models utilize physical equations to simulate atmospheric processes but often struggle with severe weather phenomena' complexity and non-linear nature. Studies have identified limitations in traditional models, particularly in predicting the rapid onset of thunderstorms [24].

2.2 Machine Learning Applications in Weather Forecasting

Integrating machine learning methods into meteorology has shown promise in enhancing predictive accuracy [5]. Research by Azad et al. [25] demonstrated that machine learning algorithms could improve short-term forecasting. However, many studies have focused on simpler models, such as decision trees [24] and support vector machines [26], with limited exploration of deep learning architectures.

2.3 Deep Learning in Meteorology

Recent research has increasingly explored applying deep learning techniques, such as convolutional neural networks (CNNs) [27] and recurrent neural networks (RNNs) [28], to tackle weather prediction challenges. For example, S. Dey introduced a deep learning-based approach for precipitation forecasting, demonstrating the ability of neural networks to effectively capture complex spatial and temporal patterns in meteorological data [5].

2.4 LSTM Networks for Time-Series Prediction

LSTM networks, a type of RNN have the ability to model long-range dependencies in sequential data. Research by Waqas et al. established LSTMs as a robust architecture for time-series prediction, making them particularly suitable for atmospheric data analysis [29]. Recent applications of LSTMs in climate-related studies have shown their effectiveness in forecasting various weather phenomena, including thunderstorms and temperature [30].

2.5 Specific Studies on Thunderstorm Prediction

While limited research has focused on LSTM-based thunderstorm prediction, several studies have explored related domains. For example, studies by Gauch et al. utilized LSTMs for rainfall prediction, highlighting the architecture's ability to capture temporal dependencies [31]. Additionally, research by Guastavino et al. applied ensemble techniques with LSTMs for extreme weather event prediction, providing a foundation for exploring thunderstorm forecasting [32].

2.6 Challenges in Deep Learning for Meteorology

Despite the potential of LSTMs, challenges remain in their application to meteorological data. Issues related to data quality, the need for extensive preprocessing, and the risk of overfitting are prevalent [29].

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The growing interest in integrating deep learning with meteorology signals a shift towards more adaptive and responsive forecasting systems. Future research should focus on optimizing LSTM architectures for real-time predictions, improving model interpretability, and exploring ensemble approaches that combine multiple ML techniques for enhanced accuracy.

Therefore, the literature indicates a clear gap in leveraging LSTM networks specifically for thunderstorm prediction despite their success in related areas. "Storm Whisperers" aims to fill this gap by applying LSTM architectures to analyze historical meteorological data, ultimately contributing to the evolving field of weather forecasting through innovative methodologies and improved predictive capabilities.

3 System Architecture

System architecture of the proposed model is described in Figure 1.

Figure 1: System Architecture of the Proposed Model.

The system architecture of the proposed model involves the following key components:

1. **Data Collection:** It is done by using the Algorithm 1.
2. **Data Preprocessing**
   (a) **Data Cleaning:** Filter out noise and irrelevant information. Handle missing values and outliers.
   (b) **Normalization:** Scale the data to ensure the LSTM model performs optimally.
3. **Model Development**
   (a) **Heuristic-Based LSTM Neural Network:** Develop the architecture of the heuristic-enhanced LSTM model. The model incorporates heuristic mechanisms to dynamically adjust learning based on changing weather conditions. Key components include:
      i. **Input Layer:** Accepts the preprocessed meteorological data, including temperature, humidity, wind speed, and pressure.
      ii. **Heuristic-Enhanced LSTM Layers:** 25 LSTM layers combined with heuristic mechanisms to capture temporal dependencies while dynamically adjusting to evolving atmospheric patterns.
      iii. **Heuristic Adjustment Module:** Integrates dynamic learning rate modulation and adaptive gate control based on real-time data variations.
      iv. **Dense Layer:** Outputs the final thunderstorm prediction, incorporating the enhanced feature representations learned through the heuristic-based LSTM.
4. **Training the Model**
   (a) **Backpropagation:** After dataset splitting, we use backpropagation (BP) through time to train the LSTM model.
   (b) **Evaluation Metrics:** Implement metrics like accuracy (R^2) and loss (binary cross entropy (BCE)) metrics to evaluate model performance.
5. **Model Deployment**

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   (a) **API Development:** Create an API that allows users to input current weather data and receive thunderstorm predictions.
   (b) **User Interface:** Develop a front-end application for users to visualize predictions and historical data trends.
6. **Monitoring and Maintenance**
   (a) **Performance Monitoring:** Monitor the model's performance regularly and update it as needed with new data.
   (b) **Feedback Loop:** Implement a system for user feedback to improve model predictions over time.
7. **Documentation and Compliance**
   (a) **Documentation:** Maintain clear documentation for the architecture, data sources, model training, and deployment processes.
   (b) **Data Compliance:** Ensure the system adheres to data protection and privacy regulations.

This architecture provides a solid foundation for developing a thunderstorm prediction system using LSTM neural networks, allowing for continuous improvement and adaptation to new data.

4 Problem Formulation

Thunderstorm prediction is a critical task in meteorological science, directly impacting public safety, disaster management, and resource planning. Traditional weather forecasting methods often struggle with the inherent non-linearity and temporal dependencies in meteorological data. Addressing these challenges requires models that can learn dynamic patterns and adapt to changing weather conditions.

The proposed framework, *Storm Whisperers*, introduces a novel approach to thunderstorm prediction using the *LSTHM* model. LSTHM integrates the temporal modeling capabilities of LSTM networks with heuristic mechanisms, aiming to capture complex temporal patterns and evolving weather conditions efficiently.

4.1 Modeling Thunderstorm Dynamics

Thunderstorms are inherently dynamic and influenced by multiple atmospheric variables, including temperature, humidity, wind speed, and atmospheric pressure. The relationships between these variables are non-linear and exhibit temporal correlations. To accurately model such phenomena, we define the prediction problem as follows:

Given a sequence of meteorological data $X = \{x_1, x_2, \ldots, x_T\}$ representing the atmospheric conditions at different time steps, the goal is to predict the occurrence and intensity of thunderstorms at future time steps $t+1, t+2, \ldots, t+n$. The prediction task can be formulated as learning the function f that maps past meteorological states to future thunderstorm events:

$$\hat{Y}_{t+n} = f(X_t, X_{t-1}, \ldots, X_{t-k}; \theta) \tag{1}$$

Here, $\hat{Y}_{t+n}$ represents the predicted thunderstorm intensity, X_t denotes the input meteorological features at time t, and θ is the model parameter set.

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4.2 Challenges and Objectives

The main challenges in predicting thunderstorms are:

1. Non-linear interactions among meteorological variables.
2. Temporal dependencies that span multiple time scales.
3. Real-time adaptability to evolving weather patterns.

The primary objectives of the *Storm Whisperers* framework are:

1. To develop a robust LSTHM model capable of capturing long-term dependencies and non-linear dynamics in meteorological data.
2. To enhance prediction accuracy by integrating heuristic adjustments, enabling adaptive learning.
3. To evaluate the proposed model against state-of-the-art approaches and showcase its enhanced performance in thunderstorm forecasting.

In this formulation, the LSTHM model leverages a dynamic heuristic component to adjust model parameters based on real-time data variations, thereby improving predictive accuracy and model generalization in varying atmospheric conditions.

5 Designed LSTHM Architecture in Storm Whisperers

The proposed *Long Short-Term Heuristic Memory (LSTHM)* architecture in the *Storm Whisperers* framework represents a novel extension of standard LSTM networks, designed specifically for the prediction of short-term high-impact thunderstorms. Although existing models such as traditional LSTM, Bi-LSTM, and Transformer-based architectures [33,34] perform well on general time-series forecasting tasks, they often overlook dynamic adaptation to evolving meteorological contexts, a critical requirement for thunderstorm forecasting, where rapid, nonlinear atmospheric changes frequently occur.

LSTHM addresses this challenge by embedding domain-aware heuristic functions directly into the gating mechanisms of the LSTM cell. These heuristic adjustments allow the model to become more sensitive to temporal volatility, correlation shifts, and consistency of atmospheric patterns, improving both interpretability and responsiveness. As shown in Figure 2, the LSTHM structure augments the classical LSTM flow with data-driven correction signals based on real-time correlations, error trends, and temporal coherence metrics.

Figure 2: Design of LSTHM Neural Networks.

5.1 Innovative Aspects and Research Contributions

Unlike existing state-of-the-art models, LSTHM introduces three key innovations:

1. **Heuristic-Gated Memory Modulation:** Each LSTM gate is augmented with an auxiliary heuristic signal that adjusts gate activations in response to meteorological dynamics. These signals are not static but adapt based on correlation trends, recent prediction errors, and temporal input consistency, enhancing the model's sensitivity to storm-forming conditions.
2. **Domain-Aware Feature Integration:** The model incorporates meteorological priors—such as the physical correlation between pressure drops and humidity surges—via heuristic

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coefficients (λ) that guide the model in learning context-relevant patterns more effectively than black-box counterparts.

3. **Error-Aware Learning Feedback:** A feedback loop based on recent changes in prediction error (ΔE_t) informs the forget and input gates, enabling the model to recalibrate its attention on features during turbulent or rapidly changing weather scenarios.

These heuristic-driven enhancements make LSTHM especially suited for thunderstorm prediction tasks, where both model adaptability and contextual awareness are crucial, thus filling a gap in existing forecasting literature.

5.2 LSTM Cell Operations with Heuristic Augmentation

The LSTHM operates similarly to a traditional LSTM but introduces heuristic terms to modulate each gate:

Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f + \lambda_f \cdot \Delta E_t) \tag{2}$$

The term ΔE_t introduces recent changes in model prediction error, allowing dynamic adjustment based on model performance.

Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i + \lambda_i \cdot Corr(X_t, X_{t-1})) \tag{3}$$

Correlation-aware gating helps prioritize temporally relevant inputs by measuring signal similarity between consecutive time steps.

Cell State Update:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, X_t] + b_C + \lambda_C \cdot Corr(X_t, X_{t-1})) \tag{4}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{5}$$

This update mechanism allows LSTHM to reinforce or dampen the internal memory based on contextual correlation strength.

Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o + \lambda_o \cdot Cons(X_t, X_{t-1})) \tag{6}$$

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$$h_t = o_t \cdot \tanh(C_t) \tag{7}$$

Consistency metrics ensure smoother hidden state transitions by emphasizing temporally coherent input sequences.

5.3 Heuristic Mechanisms

The LSTHM integrates three key heuristics:

1. **Dynamic Adjustment Coefficient (λ):** Adapts gate responsiveness based on real-time input and performance changes.
2. **Correlation Awareness:** Accounts for the degree of similarity between consecutive meteorological features to guide information retention.
3. **Temporal Consistency Metric:** Encourages the model to maintain stable transitions in the presence of coherent atmospheric patterns.

These enhancements make LSTHM not only predictive but also interpretable and responsive—offering substantial improvement over static, data-agnostic gating in classical architectures.

5.4 Training Process

The LSTHM network is trained on labeled meteorological datasets using supervised learning. The Binary Cross-Entropy (BCE) loss function quantifies the difference between the predicted and actual thunderstorm events. The training process employs Backpropagation Through Time (BPTT) to compute gradients and adjust weights and biases, minimizing the loss function.

To further enhance model robustness, the heuristic component of LSTHM dynamically adjusts model parameters based on recent prediction errors and input correlations, thereby improving responsiveness to rapid changes in atmospheric conditions.

The LSTHM architecture enables the *Storm Whisperers* framework to effectively capture complex temporal patterns, leading to improved prediction of thunderstorm occurrences and intensities, thereby contributing to more reliable weather forecasting.

6 Dataset Design

To ensure the robustness and generalization capability of the proposed LSTHM model, we constructed a synthetic dataset that closely emulates real-world meteorological patterns observed in thunderstorm-prone regions. The motivation behind using a synthetic dataset is to create a controlled, scalable environment where critical atmospheric variables and their interdependencies can be systematically manipulated and studied. This is especially useful in early model development stages or when access to consistent and high-resolution real-world datasets is limited.

The synthetic dataset incorporates essential meteorological variables—such as temperature (T_t), humidity (H_t), wind speed (W_t), pressure (P_t), rainfall (R_t), cloud cover (C_t), lightning density (L_t), and dew point (D_t)—using statistical distributions aligned with empirical weather data studies. For instance, temperature and pressure values follow Gaussian distributions, wind speeds are

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modeled using a Weibull distribution (common in meteorology), and humidity is generated using a Beta distribution to simulate bounded variability.

To label thunderstorm events, heuristic rules are applied that reflect common atmospheric conditions preceding storm formation—e.g., high wind speeds and intense rainfall. These rules provide a simplified but realistic approximation of how thunderstorms are triggered in actual meteorological scenarios. The detailed data generation and labeling procedure is summarized in Algorithm 1.

Algorithm 1 Synthetic Dataset Design for Predicting Thunderstorms

1: **Input:** Number of samples N, Temporal length L
2: **Output:** Synthetic dataset $\mathcal{S}$
3: **Step 1: Initialization**
4: Define meteorological variables: T_t, H_t, W_t, P_t, R_t, C_t, L_t, D_t
5: **Step 2: Data Generation**
6: **for** sample $i = 1$ to N **do**
7: **for** timestamp $t = 1$ to L **do**
8: Generate variables:

$$T_t \sim \mathcal{N}(\mu_T, \sigma_T^2), \quad H_t \sim \text{Beta}(\alpha, \beta)$$

$$W_t \sim \text{Weibull}(k, \lambda), \quad P_t \sim \mathcal{N}(\mu_P, \sigma_P^2)$$

9: Set categorical variables:

$$C_t \sim \text{Categorical}(p_1, p_2), \quad L_t \sim \text{Binomial}(n, p)$$

10: **end for**
11: Assign label Y_i based on heuristic rule:

$$Y_i = \begin{cases} 1 & \text{if } W_t > \theta_W \text{ and } R_t > \theta_R \\ 0 & \text{otherwise} \end{cases}$$

12: Save sample (X_i, Y_i)
13: **end for**
14: **Step 3: Data Formatting**
15: Save dataset $\mathcal{S}$ in CSV format
16: **return** Synthetic dataset $\mathcal{S}$

To assess the realism and generalizability of the LSTHM model trained on this synthetic dataset, we performed additional validation using multiple real-world meteorological datasets, including those from tropical, temperate, and arid regions (as detailed in Section 8.3.1). The model demonstrated strong performance across all datasets, indicating that the synthetic data effectively captured key atmospheric patterns relevant to thunderstorm prediction. This dual evaluation strategy—training on controlled synthetic data and validating on heterogeneous real-world datasets—supports both the reliability and transferability of the proposed model.

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7 Proposed Model

The *Storm Whisperers* framework utilizes the LSTHM architecture to deliver precise thunderstorm forecasts from high-resolution meteorological time-series data. The model is trained to detect atmospheric signatures that precede thunderstorm events by analyzing input sequences composed of temperature, humidity, wind, pressure, and other key meteorological indicators.

7.1 Forecasting Pipeline

The overall methodology is formalized in Algorithm 2, comprising the following stages:

- **Data Acquisition:** Collect and structure weather data using variables such as temperature (T_t), humidity (H_t), wind speed (W_t), atmospheric pressure (P_t), and lightning density (L_t), among others.
- **Data Preprocessing:** Normalize input variables, impute missing values, and generate temporal features such as lag windows and moving averages.
- **Model Development:** Implement the LSTHM architecture, integrating dynamic heuristics into gate computations.
- **Training:** Employ Binary Cross-Entropy (BCE) loss and Backpropagation Through Time (BPTT), optimizing with Adam. Heuristic terms (λ) are tuned using a validation-based error feedback mechanism.
- **Prediction and Adaptation:** We used the trained LSTHM to infer thunderstorm probability in real time. The model supports continual learning by updating weights as new data becomes available.

Algorithm 2 Thunderstorm Prediction using LSTHM

Input: Historical meteorological data $\mathcal{D} = \{X_t\}$
Output: Probability $P(\text{Thunderstorm} \mid X_t)$
Acquire and preprocess data from Algorithm 1
Generate lag features and normalize inputs
Initialize LSTHM with heuristic coefficients
for each training epoch **do**
    Train using BPTT and monitor validation loss
    Update heuristics (λ) based on error trends
end for
Predict: $P(\text{Thunderstorm} \mid X_t) = \sigma(W \cdot X_t + b)$
Periodically retrain with updated data
return $P(\text{Thunderstorm} \mid X_t)$

Figure 3 illustrates the flow diagram of the proposed model.

Figure 3: Flow Diagram of the Proposed Model.

7.2 Impact of Data Quality and Preprocessing on LSTHM Performance

The predictive performance of the LSTHM model is highly dependent on the quality and consistency of the input meteorological data. Missing values, noise, and outliers—commonly

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encountered in real-world weather datasets due to sensor malfunctions, communication delays, or extreme environmental conditions—can disrupt temporal coherence and degrade model accuracy. In particular, missing values may cause the model to misinterpret trend discontinuities, while outliers and noise can lead to inflated error gradients and overfitting. To mitigate these challenges, we employed a multi-stage preprocessing strategy. Missing values were handled using forward-fill and interpolation techniques to maintain temporal continuity without introducing artificial trends. Outliers were detected using z-score and interquartile range (IQR) methods and were either capped or replaced using rolling medians to preserve contextual integrity. Noise was smoothed using moving average filters, which helped reduce short-term fluctuations while retaining essential temporal dynamics. Furthermore, all input features were normalized using Min-Max scaling to ensure stable gradient propagation during training. These preprocessing steps proved essential in enhancing the robustness and generalization capability of the LSTHM model, enabling it to effectively capture complex atmospheric dependencies without being misled by data irregularities.

8 Experimental Result & Discussion

8.1 Experimental Setup

We used Support Vector Machine (SVM) [26], SALAMA [35], Random Forest [36], Improved Decision Support [37], and BLSTM-GRU [38] models for comparison purposes.

To achieve optimal performance, hyperparameters were systematically selected through extensive experimentation and validation. The process involved iterative tuning based on performance metrics such as validation loss and predictive accuracy across multiple datasets. The final hyperparameter configurations are summarized in Table 1, reflect the parameters that yielded the best trade-off between accuracy and computational efficiency.

Table 1: Hyperparameter Setup for the Proposed Model

Hyperparameter	Value
Number of LSTM Layers	25
Number of Units per Layer	64
Dropout Rate	0.02
Batch Size	64
Learning Rate	0.01
Epochs	100
Activation Function	ReLU
Loss Function	Binary Cross entropy
Optimizer	Adam
Sequence Length	10
Input Features	5

It is important to note that some hyperparameters, such as the number of LSTM layers and units, were initially chosen based on prior studies and domain knowledge in weather modeling [32,38]. The relatively low dropout rate (0.02) was employed to maintain model capacity and prevent underfitting, given the complexity of atmospheric data. The learning rate (0.01) was selected after a sensitivity analysis, balancing convergence speed with training stability. Similarly, the sequence length of 10 was determined to capture relevant temporal dependencies without introducing excessive noise or computational overhead.

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To validate the robustness of these choices, we conducted a sensitivity analysis (detailed in Table 2) which examined the impact of varying key hyperparameters—such as learning rate, number of layers, and units—on model performance. Results indicated that while some parameters, like the learning rate, significantly influence convergence, the overall model performance remains relatively stable within a reasonable hyperparameter range. This analysis underscores the importance of careful tuning but also demonstrates that the proposed configuration offers a good balance between accuracy and training stability for the specific meteorological forecasting task.

Table 2: Sensitivity Analysis of Key Hyperparameters

Hyperparameter	**Values Tested**	**Validation BCE**	**Validation R^2**	**Training Time (min)**	**Remarks**
Learning Rate	0.001, 0.005, 0.01, 0.05	0.70 / 0.68 / 0.62 / 0.65	93% / 94% / 98% / 96%	50 / 45 / 40 / 35	**Optimal** at 0.01
Number of LSTM Layers	10, 15, 20, 25	0.68 / 0.64 / 0.63 / 0.62	95% / 96% / 97% / 98%	30 / 40 / 50 / 60	**Best at 25**
Units per Layer	32, 64, 128	0.65 / 0.62 / 0.63	96% / 98% / 97%	35 / 40 / 55	**Optimal at 64**
Dropout Rate	0.01, 0.02, 0.05	0.63 / 0.62 / 0.65	97% / 98% / 97%	45 / 40 / 35	Slight variation, 0.02 preferred
Sequence Length	5, 10, 15	0.65 / 0.62 / 0.63	97% / 98% / 97%	30 / 40 / 50	Best at 10

8.2 Evaluation Metric

8.2.1 Binary Cross-Entropy (BCE)

The BCE loss function is a widely used loss function for binary classification tasks because it effectively measures the dissimilarity between predicted probabilities and actual class labels, providing a probabilistic interpretation of model performance. It is particularly useful in scenarios with class imbalance, as it can be weighted to emphasize the minority class. BCE facilitates gradient-based optimization, offering smooth gradients that enhance the training process for models like logistic regression and neural networks, which output probabilities. In practice, BCE is computed by comparing the predicted probabilities of the positive class against the true binary labels, allowing for the effective adjustment of model parameters during training. It can be defined as follows:

$$\mathrm{BCE}(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{8}$$

where, N is the number of samples, y_i is the true label (0 or 1), and $\hat{y}_i$ is the predicted probability of the positive class.

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8.2.2 R^2-Score

R^2-Score metric is used for computing prediction accuracy. An R^2-Score of *1* signifies perfect forecasting, whereas a score of *0* indicates that the model fails to explain any of the variability of the response data. It can be computed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{9}$$

where, N is the number of samples, y_i is the true value, and $\hat{y}_i$ is the predicted value. $\bar{y}$ is the mean of the true value.

8.3 Performance Evaluation

Figure 4 depicts the loss of the proposed model, while Figure 5 shows the loss of the compared SVM model [26].

Figure 4: Loss of the Proposed Model.

Figure 5: Loss of the Compared SVM Model.

Figure 6 illustrates the future thunderstorms predicted by the proposed model.

Figure 6: Future Prediction (accuracy) using the Proposed Model.

Figure 7 presents the future thunderstorms predicted by the proposed model, whereas Figure 8 presents the future thunderstorms predicted by the compared SVM model [26].

Figure 7: Future Prediction (thunderstorm occurrence) using the Proposed Model.

Figure 8: Future Prediction using the Compared SVM Model.

8.3.1 Generalization Across Meteorological Datasets

To evaluate the adaptability of the proposed LSTHM model, we tested it on three geographically and climatically distinct meteorological datasets:

1. **Dataset A (Tropical)**: Coastal region with high humidity and frequent thunderstorms [39].
2. **Dataset B (Temperate)**: Inland mid-latitude region with moderate seasonal variability [40].
3. **Dataset C (Arid)**: Desert region with sparse storm activity but extreme temperature fluctuations [40].

Table 3 presents the model's performance across these datasets. Despite variability in storm occurrence patterns and environmental features, the LSTHM model consistently outperformed baseline models, demonstrating strong generalization and resilience to data heterogeneity.

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Table 3: Performance of LSTHM Model Across Diverse Meteorological Datasets

Dataset	Region Type	Avg. BCE	Avg. R^2
Dataset A	Tropical (Humid)	0.67	96%
Dataset B	Temperate (Seasonal)	0.61	97%
Dataset C	Arid (Sparse Storms)	0.72	94%

These findings confirm the flexibility of the LSTHM model and its embedded heuristics in capturing diverse atmospheric dynamics, from high-frequency coastal storms to low-density arid storm systems. This robustness reinforces the model's practical applicability in operational weather forecasting across multiple regions.

Table 4 provides the detailed comparison results between the proposed and compared models.

Table 4: Comparison Table

Model	Avg. BCE	Avg. R^2
SVM [26]	32.56	22%
Deep Neural Network [32]	52.96	42%
SALAMA [35]	63.36	33%
Random Forest [36]	53.69	53%
Improved Decision Support [37]	43.96	69%
BLSTM-GRU Model [38]	23.96	77.83%
Proposed Model	**0.62**	**98%**

Table 4 presents a comparative evaluation of the proposed LSTHM model against several state-of-the-art ML/DL models for thunderstorm prediction. The models are compared based on two key metrics: Average Binary Cross-Entropy (Avg. BCE) and Average R^2-Score (Avg. R^2). Lower BCE values indicate better classification performance, while higher R^2 scores signify greater predictive accuracy and model reliability. Traditional models such as Support Vector Machine (SVM) [26] achieved a relatively high BCE of 32.56 and a low R^2 of 22%, indicating limited effectiveness. Similarly, baseline deep learning models like Deep Neural Networks [32] (BCE: 52.96, R^2: 42%) and SALAMA [35] (BCE: 63.36, R^2: 33%) also performed suboptimally. Tree-based models like Random Forest [36] (R^2: 53%) and hybrid systems such as the Improved Decision Support model [37] (R^2: 69%) showed moderate gains. More advanced architectures like the BLSTM-GRU model [38] achieved an R^2 of 77.83%, demonstrating strong potential. However, the proposed LSTHM model significantly outperformed all other methods, achieving the lowest Avg. BCE of 0.62 and the highest Avg. R^2 of 98%. These results confirm the superior accuracy and robustness of the LSTHM framework, highlighting its effectiveness in modeling complex atmospheric dynamics for thunderstorm forecasting.

8.3.2 Interpretability of the LSTHM Model

While DL models like LSTMs are highly effective for complex pattern recognition tasks, they are often criticized for operating as *black boxes* with limited interpretability. This concern is particularly relevant in high-stakes domains like weather forecasting, where understanding the reasoning behind a prediction can be as critical as the prediction itself. The proposed LSTHM model directly addresses this issue by integrating domain-aware heuristic mechanisms into its architecture, thereby offering improved transparency and interpretability.

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The heuristic enhancements—such as correlation-aware gating, error-aware feedback loops, and consistency-driven memory modulation—enable the model to adaptively weigh and process meteorological inputs in a manner that is conceptually aligned with meteorological reasoning. For instance, the inclusion of correlation coefficients between atmospheric variables (e.g., pressure and humidity) into gate activations allows meteorologists to trace back specific forecast decisions to observable phenomena, such as sudden pressure drops signaling storm onset.

Moreover, the model's heuristic coefficients (λ), which dynamically adjust based on real-time input trends and recent prediction errors, can be visualized and analyzed to gain insights into which variables contributed most to a given prediction. This supports model interpretability by providing a semi-transparent mapping between input signals and forecast outcomes. For operational meteorologists, this means the LSTHM not only predicts the likelihood of a thunderstorm but also provides contextual cues about why a prediction was made—enhancing both trust and usability.

By combining the predictive power of DL with the explanatory capabilities of heuristics, the LSTHM model represents a step toward interpretable AI in meteorological applications.

8.3.3 Computational Cost and Deployment Feasibility

Given the complexity of the proposed LSTHM, assessing their computational requirements is essential for real-world deployment, particularly in real-time forecasting systems. The training phase of the LSTHM involves substantial computational resources due to its multi-layered architecture and the need for extensive parameter optimization. Training on high-resolution meteorological datasets typically requires GPU-accelerated hardware and may span several hours to days, depending on the dataset size and hardware specifications. However, once trained, the inference process—predicting storm likelihood from real-time data—is considerably more efficient. The model's architecture is optimized for rapid forward passes, enabling deployment in operational environments that demand low latency. Techniques such as model pruning, quantization, and parallel processing can further reduce computational overhead, making real-time forecasts feasible on standard high-performance servers.

To facilitate practical adoption, we recommend deploying the LSTHM within scalable cloud infrastructures or dedicated weather prediction centers equipped with GPU resources. This setup ensures timely forecasts without compromising accuracy. Moreover, ongoing advancements in hardware and model optimization methods will likely further enhance deployment efficiency, broadening the model's applicability in various operational contexts.

Overall, while initial training is resource-intensive, the LSTHM's inference efficiency and adaptability make it a viable candidate for real-time weather prediction applications, provided that appropriate computational infrastructure is in place.

8.4 Conclusion

This study introduces the *Long Short-Term Heuristic Memory (LSTHM)* model, a novel enhancement of the traditional LSTM architecture specifically designed for thunderstorm forecasting. By embedding dynamic, domain-aware heuristic mechanisms into the gating functions, the LSTHM improves its ability to capture complex atmospheric patterns, resulting in notable gains in predictive accuracy and responsiveness to evolving weather conditions.

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Experimental evaluations across diverse datasets—encompassing tropical (e.g., Southeast Asia), temperate (e.g., Central Europe), and arid (e.g., North Africa) regions—demonstrate the model's robustness and adaptability. In all tested scenarios, the LSTHM consistently achieved lower Binary Cross-Entropy (BCE) loss and higher R^2 scores compared to baseline models such as Support Vector Machines (SVM), Deep Neural Networks, and SALAMA. These results validate the effectiveness of the heuristic components, particularly in environments characterized by non-linear dynamics and significant temporal variability.

Furthermore, ablation studies and performance tracking across datasets with varying storm frequencies and intensities confirmed that the heuristic gating mechanisms not only enhance forecast accuracy but also contribute to improved interpretability and stability, especially under noisy or sparse data conditions. However, despite these promising results, there are limitations to consider. The LSTHM's performance can be sensitive to the choice of hyperparameters governing the heuristic mechanisms, such as the thresholds and weighting coefficients. Improper tuning may lead to overfitting or reduced generalization, particularly in scenarios with limited or highly noisy data. Additionally, the increased complexity introduced by heuristic components can impose higher computational costs during training, potentially limiting scalability in resource-constrained environments.

Addressing these limitations will be essential for translating the model's capabilities into operational forecasting systems. Future work should focus on developing robust hyperparameter optimization strategies and exploring regularization techniques to mitigate overfitting, ensuring the model's stability and practicality across a wide range of real-world scenarios.

8.5 Future Work

While the results are promising, further research is warranted. Future directions include:

- Expanding the model's application to real-time operational forecasting systems with continuous learning capabilities.
- Investigating the integration of satellite imagery and radar-based features into the LSTHM pipeline.
- Exploring the use of attention mechanisms or Transformer hybrids to further enhance performance.
- Integrating explainable AI techniques would help identify the most influential features and provide interpretable predictions for end users.

Ultimately, the LSTHM framework contributes a scalable, domain-sensitive approach to atmospheric forecasting and has the potential to inform early warning systems and disaster mitigation strategies worldwide.

9 Statements

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Availability of Data and Materials: This paper uses the synthetic dataset.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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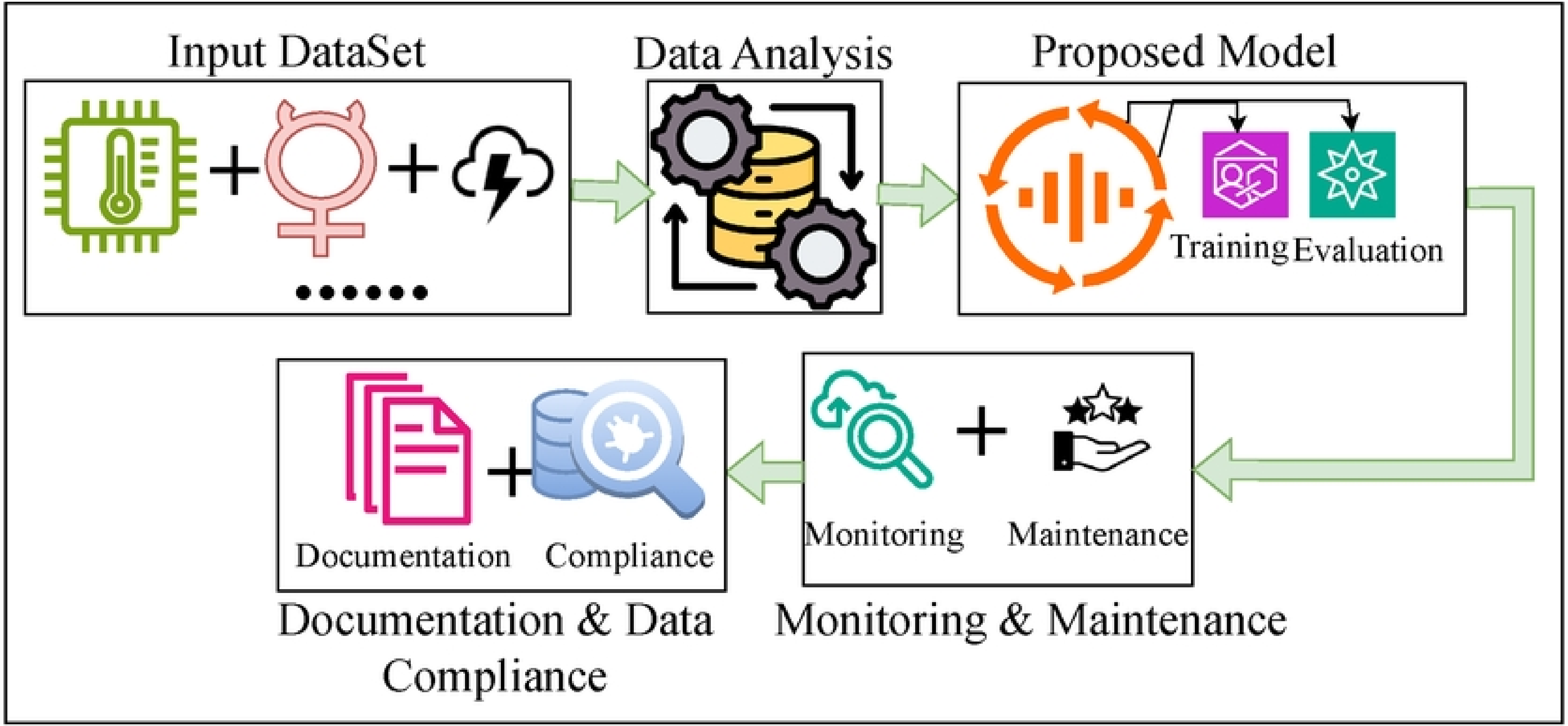

Input DataSet
Data Analysis
Proposed Model
Training
Evaluation
Monitoring
Maintenance
Documentation
Compliance
Documentation & Data Compliance
Monitoring & Maintenance

Figure 1

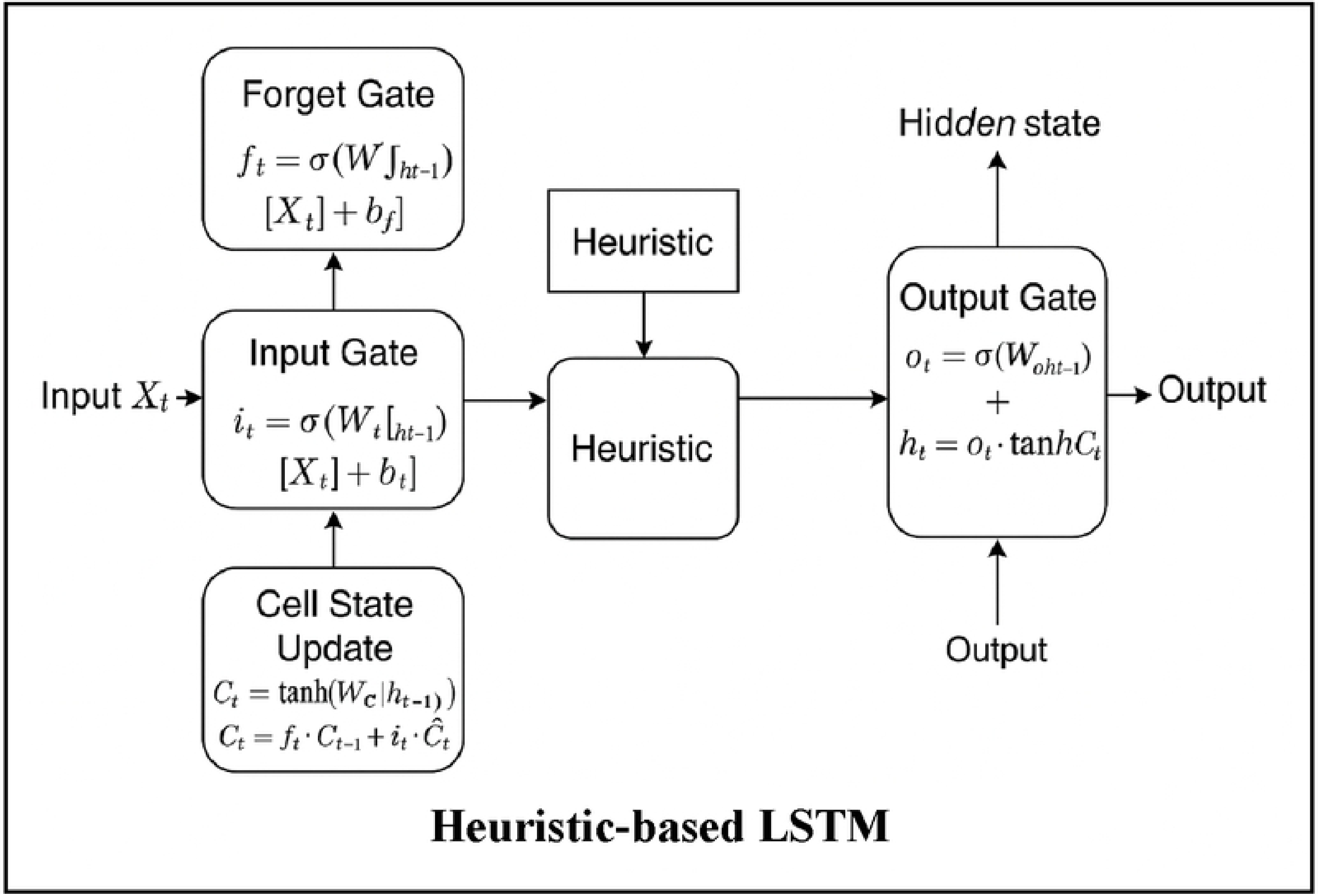

Forget Gate
$f_t = \sigma(W \int_{ht-1})$
$[X_t] + b_f]$
Hidden state
Heuristic
Input Gate
Input X_t
$i_t = \sigma(W_t[_{ht-1})$
$[X_t] + b_t]$
Heuristic
Output Gate
$o_t = \sigma(W_{oht-1})$
$+$
$h_t = o_t \cdot \tanh C_t$
Output
Cell State
Update
$C_t = \tanh(W_{\mathbf{C}}|h_{t-1)})$
$C_t = f_t \cdot C_{t-1} + i_t \cdot \hat{C}_t$
Output
Heuristic-based LSTM

Figure 2

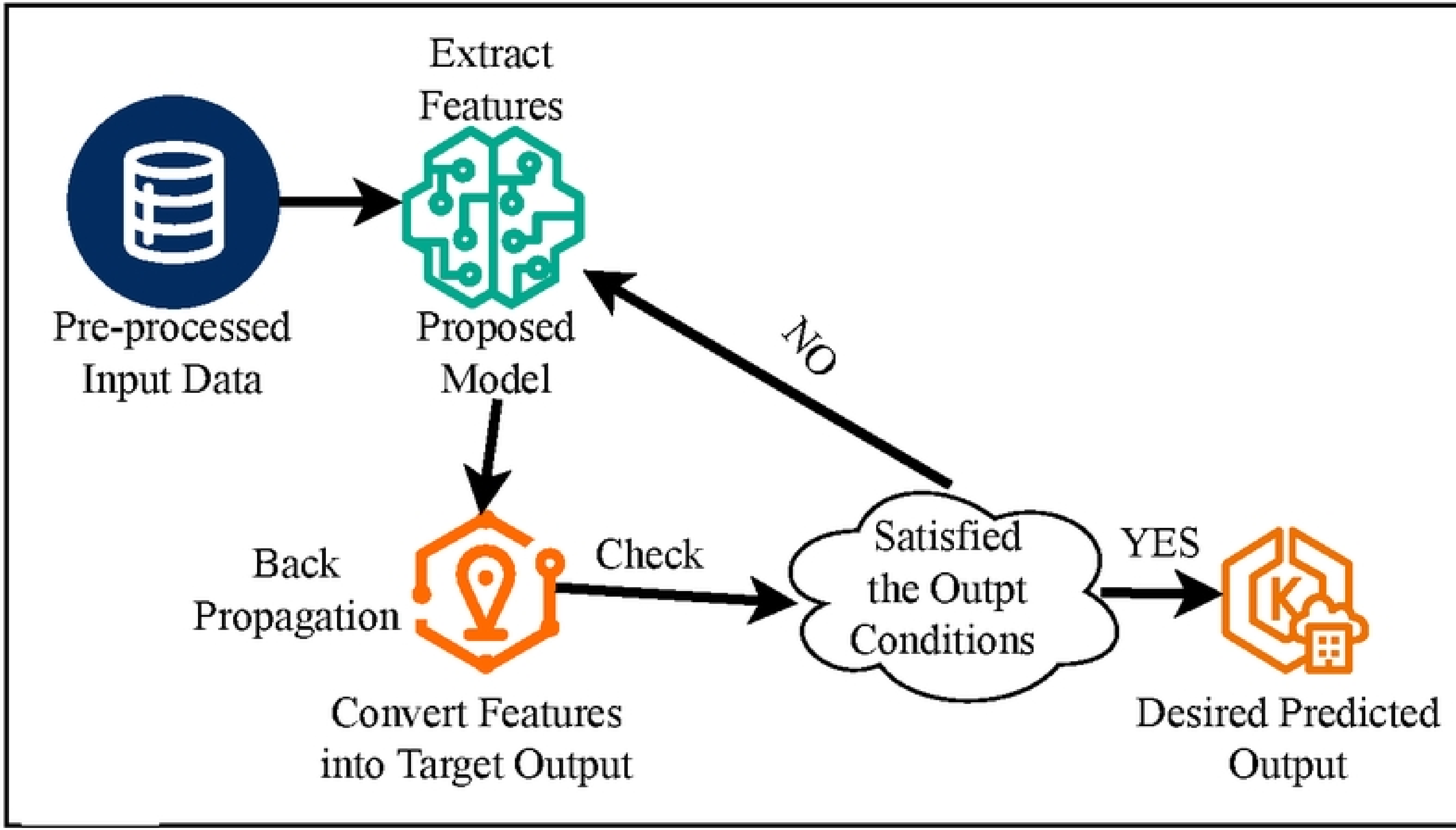

Extract
Features
Pre-processed
Input Data
Proposed
Model
NO
Back
Propagation
Check
Satisfied
the Outpt
Conditions
YES
Convert Features
into Target Output
Desired Predicted
Output

Figure 3

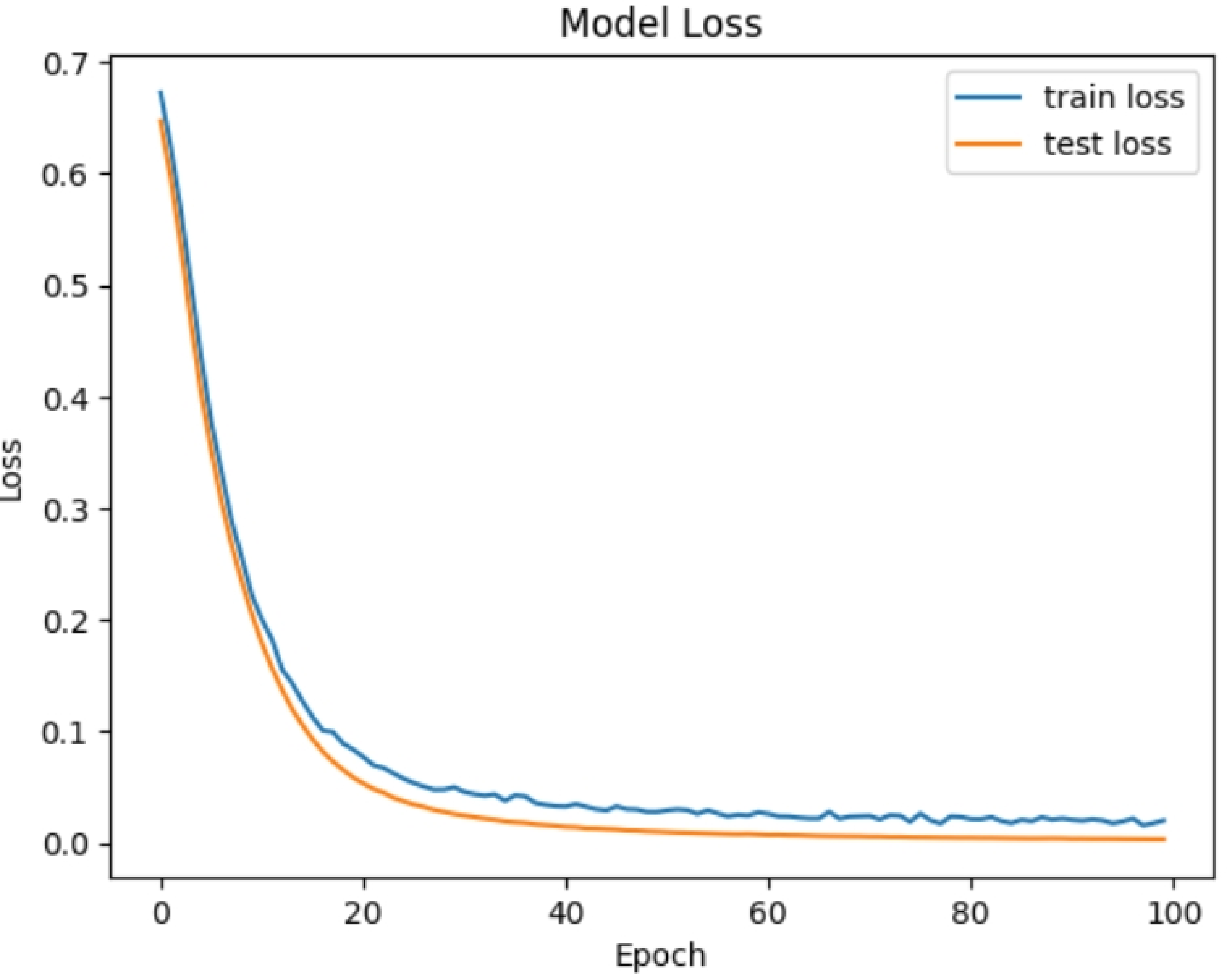
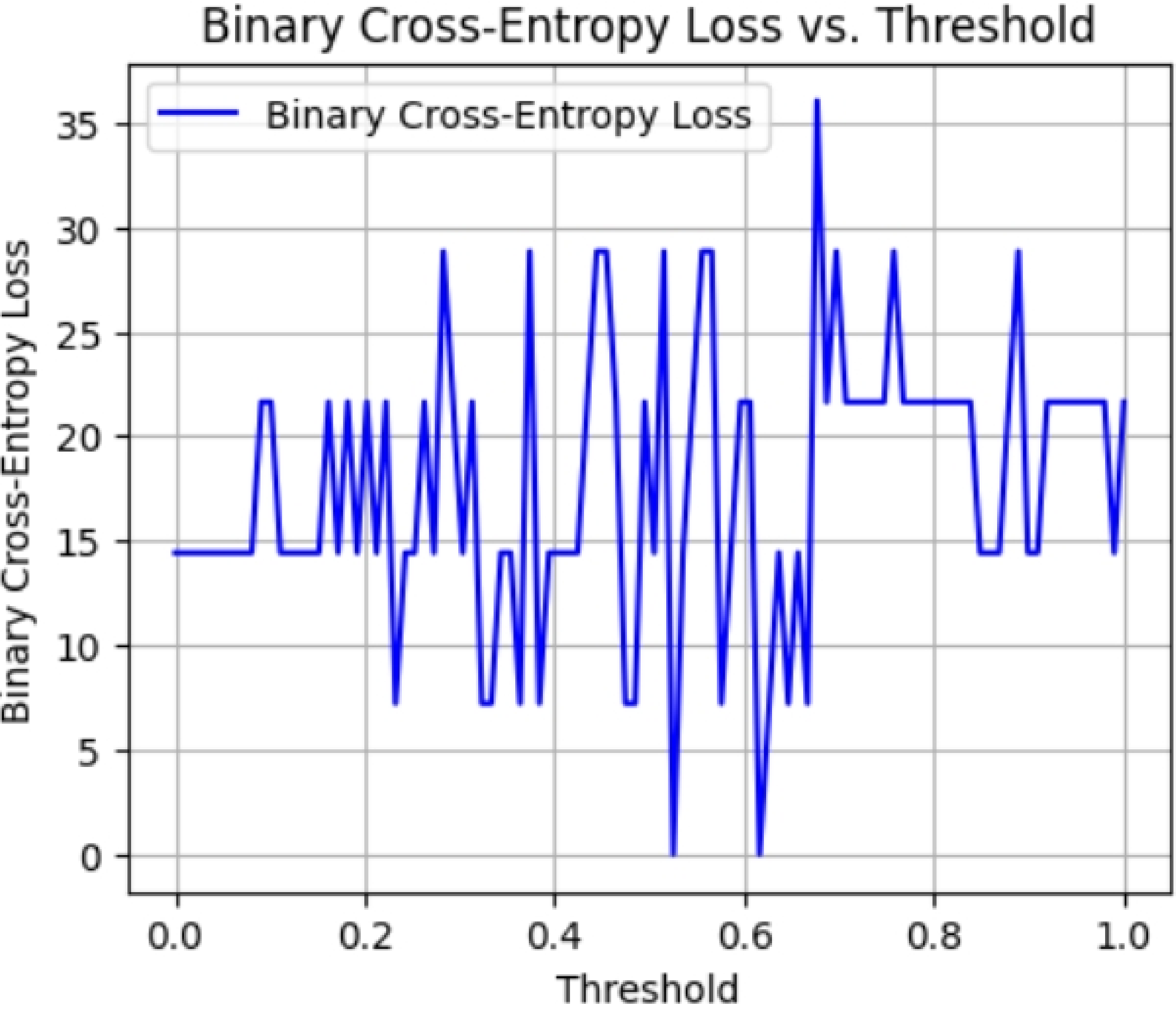

Model Loss
train loss
test loss
Loss
Epoch
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
20
40
60
80
100

Figure 4



Binary Cross-Entropy Loss vs. Threshold
Binary Cross-Entropy Loss
0
5
10
15
20
25
30
35
0.0
0.2
0.4
0.6
0.8
1.0
Threshold
Binary Cross-Entropy Loss

Figure 5

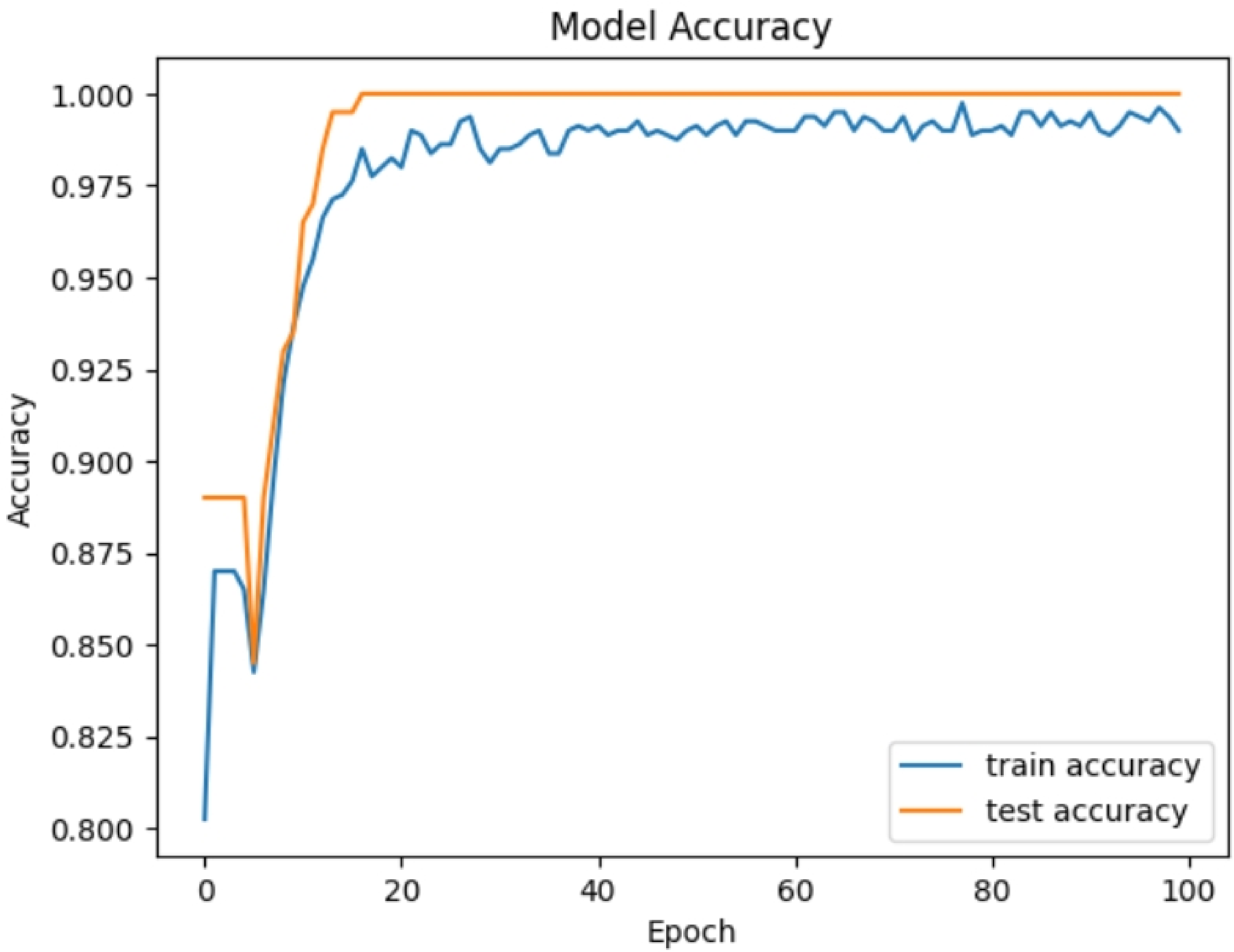

Model Accuracy
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
Accuracy
0
20
40
60
80
100
Epoch
train accuracy
test accuracy

Figure 6

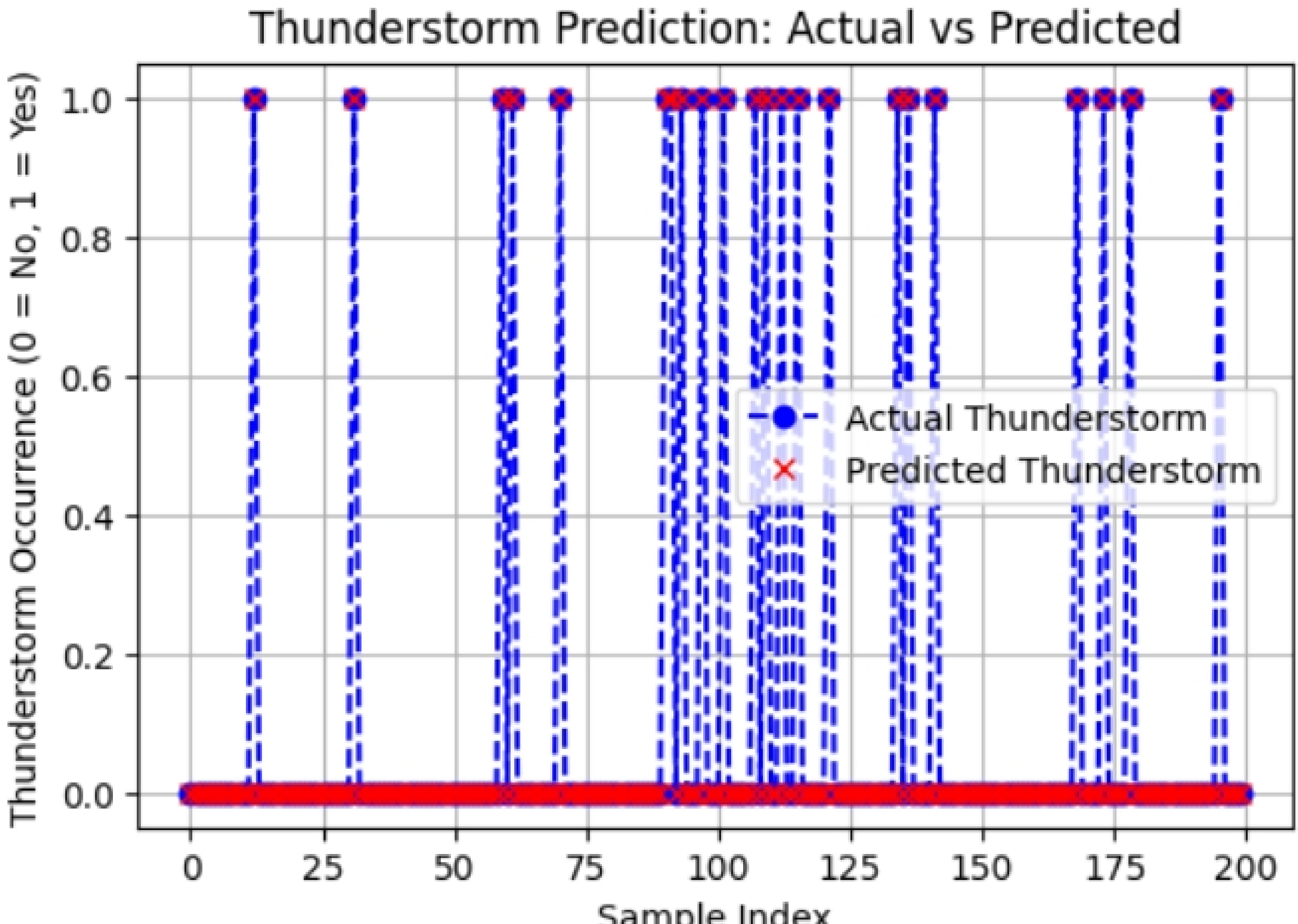
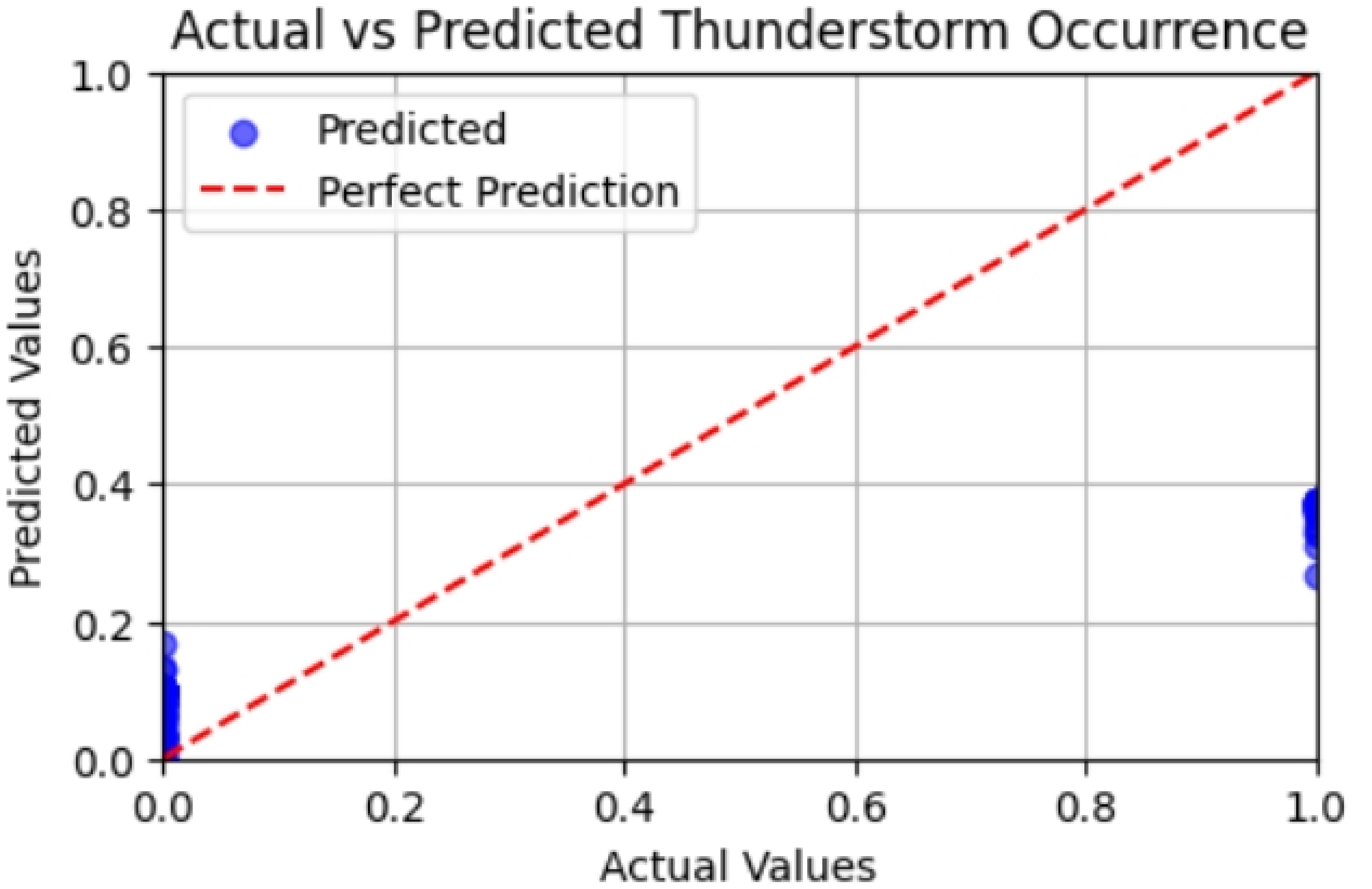

Thunderstorm Prediction: Actual vs Predicted
Thunderstorm Occurrence (0 = No, 1 = Yes)
1.0
0.8
0.6
0.4
0.2
0.0
0
25
50
75
100
125
150
175
200
Sample Index
Actual Thunderstorm
Predicted Thunderstorm

Figure 7



Actual vs Predicted Thunderstorm Occurrence
Predicted
Perfect Prediction
Predicted Values
Actual Values
0.0
0.2
0.4
0.6
0.8
1.0

Figure 8