Musik in Bayern
ISSN: 0937-583x Volume 90, Issue 12 (Dec -2025)
https://musikinbayern.com DOI **https://doi.org/10.15463/gfbm-mib-2025-525**

HYBRIDLOGINET: A DEEPLY-AUGMENTED LOGISTIC REGRESSION FRAMEWORK WITH ATTENTION FOR EXTREME WEATHER EVENT CLASSIFICATION AND PROBABILISTIC FORECASTING

Dr. M. Rathamani
Assistant Professor, PG Department of Computer Science, N.G.M College, Pollachi, Coimbatore, Tamil Nadu-642001, India. Email: rm32233@gmail.com

Dr. M. Meena Krithika
Assistant Professor, Department of Computer Science with DA, N.G.M College, Pollachi, Coimbatore, Tamil Nadu-642001, India

C. Devandran
2-Year MSc, Computer Sciene, N.G.M College, Pollachi, Coimbatore, Tamil Nadu-642001, India.

K. Dhandapani
2-Year MSc, Computer Sciene, N.G.M College, Pollachi, Coimbatore, Tamil Nadu-642001, India.

A.Karthi
2-Year MSc, Computer Sciene, N.G.M College, Pollachi, Coimbatore, Tamil Nadu-642001, India.

To Cite this Article

Dr. M. Rathamani, Dr. M. Meena Krithika, C. Devandran, K. Dhandapani, A. Karthi. **HYBRIDLOGINET: A DEEPLY-AUGMENTED LOGISTIC REGRESSION FRAMEWORK WITH ATTENTION FOR EXTREME WEATHER EVENT CLASSIFICATION AND PROBABILISTIC FORECASTING.** *Musik In Bayern, Vol. 90, Issue 12, Dec 2025, pp 459-465*

Article Info

Received: 09-09-2025 Revised: 19-10-2025 Accepted: 12-11-2025 Published: 30-12-2025

Abstract:
Numerical Weather Prediction (NWP) models, while physically comprehensive, are computationally prohibitive for real-time, high-resolution forecasting of localized extreme weather events. Traditional statistical methods like Logistic Regression (LR) offer interpretability and probabilistic outputs but lack the capacity to model complex, non-linear atmospheric patterns. This paper introduces HybridLogiNet, a novel deep learning architecture that fundamentally re-engineers the classical logistic regression algorithm by augmenting it with deep feature extraction and temporal attention mechanisms. The core innovation lies in replacing the simple linear weighted sum of LR ($z = w \cdot x + b$) with a deep, non-linear feature transformation network, while preserving the final sigmoid-activated logistic layer for inherently probabilistic, interpretable classification. HybridLogiNet employs a 1D Convolutional Neural Network (CNN) branch to extract spatial patterns from high-dimensional reanalysis grids (ERA5) and a Bidirectional LSTM branch to capture temporal dependencies in meteorological time series. A Cross-Attention Transformer Module dynamically fuses these spatiotemporal representations, with the resulting context vector serving as the sophisticated input to the final logistic classification layer. The model is specifically tasked with binary and multi-class prediction of high-impact events: thunderstorms, extreme precipitation (>50mm/24h), and heatwaves. Trained and validated on a 40-year (1980-2020) global dataset, HybridLogiNet outperforms both standard LR and modern deep classifiers (ResNet, Transformer). For 24-hour thunderstorm prediction, it achieves an F1-Score of 0.91 and a Brier Skill Score of 0.42, significantly exceeding the 0.71 F1 and 0.18 BSS of LR. Crucially, the model maintains the calibrated probability estimates critical for risk communication, while the attention

weights provide meteorologically interpretable insights into salient features (e.g., identifying convective instability precursors). This work demonstrates that deep learning can be surgically integrated into classic statistical frameworks to create a new class of models that are both highly accurate and decision-ready, bridging the gap between black-box complexity and operational utility in weather forecasting.

Keywords:
Deep Learning, Logistic Regression, Weather Prediction, Extreme Weather Classification, Explainable AI (XAI), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Attention Mechanism, Probabilistic Forecasting, Hybrid Models.

1. Introduction

Accurate and timely prediction of high-impact weather events is a grand challenge with profound implications for public safety, economic security, and disaster preparedness [1]-[3]. The operational forecasting ecosystem is dominated by two disparate paradigms: (1) Physics-based Numerical Weather Prediction (NWP) models, which solve discretized fluid dynamics equations but are resource-intensive and suffer from initial condition uncertainty, and (2) Statistical/Model Output Statistics (MOS) methods, which post-process NWP outputs using historical relationships. Classic Logistic Regression (LR) is a cornerstone of MOS for probabilistic event forecasting (e.g., PoP - Probability of Precipitation) due to its simplicity, interpretability, and natural provision of well-calibrated probabilities [4]-[5].

However, LR is fundamentally limited. While deep learning models—notably Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—have shown remarkable success in learning these complex patterns directly from data, they often function as "black boxes," producing less calibrated probability estimates and offering limited insight into the drivers of a specific forecast. This creates a critical gap: operational meteorologists require both high accuracy *and* interpretable, trustworthy probabilistic guidance to make confident decisions [6]-[10].

This research posits that the future of operational statistical forecasting lies not in abandoning classic, interpretable frameworks, but in radically enhancing their capacity with deep learning. We propose HybridLogiNet, a hybrid model that redefines the logistic regression paradigm. Instead of applying LR to raw or hand-engineered features, we use a deep neural network as a universal, adaptive feature extractor. This "deep feature engine" transforms high-dimensional, gridded atmospheric data into a rich, non-linear latent representation. This representation is then fed into a single logistic layer (sigmoid/softmax), preserving the probabilistic and partially interpretable output structure that forecasters trust. The model's architecture is explicitly designed to provide insights via attention mechanisms, revealing *which* spatial regions and *which* temporal lags most influenced a specific prediction.

The core research questions are:

1. Can a deep learning architecture be structurally integrated with the logistic function to create a model superior to both standalone LR and monolithic deep networks for weather classification tasks?
2. Does this hybrid approach retain the probability calibration advantages of LR while matching the predictive power of state-of-the-art deep classifiers?
3. Can the internal attention mechanisms yield meteorologically plausible explanations for predictions, enhancing forecaster trust and utility?

This paper details the HybridLogiNet architecture, validates its performance on global extreme weather datasets, and argues for its role as a next-generation tool in the meteorologist's arsenal.

2. Methodology

2.1 Problem Formulation & Data

We frame weather prediction as a supervised classification task. For a given location and target time (t+24h), the model predicts the probability of an event class *y* (e.g., y ∈ {Thunderstorm, No Thunderstorm}) given a spatiotemporal context window.

- **Input Data:** Multivariate meteorological fields from the ERA5 reanalysis dataset on a 0.25° grid. Variables include: geopotential at 500hPa, mean sea level pressure, 2m temperature, specific humidity at 850hPa, U/V wind components at 10m and 500hPa, and convective available potential energy (CAPE). For each prediction point, we extract a 20x20 grid (spatial) over the preceding 72 hours at 6-hour intervals (temporal), creating a 4D tensor: [Variables, Time, Lat, Lon].
- **Target Labels:** Binary/multi-class labels derived from ERA5-convective rainfall, lightning observation databases (GLD360), and extreme temperature indices.

2.2 The HybridLogiNet Architecture

The architecture consists of three core components: a Deep Feature Extractor, an Attention-based Fusion and Contextualizer, and the Logistic Classification Head.

1. Deep Feature Extractor:

- **Spatial Pathway (1D-CNN):** Each meteorological variable's spatial grid at each time step is processed by parallel 1D convolutional layers applied to latitude and longitude dimensions, followed by a 2D convolution. This captures synoptic-scale patterns (e.g., pressure gradients, frontal boundaries).
- **Temporal Pathway (Bi-LSTM):** The time series of each variable at each grid point (or of spatially aggregated features) is fed into a Bidirectional LSTM. This captures temporal evolution and persistence (e.g., moisture advection, cooling trends).

2. Cross-Attention Fusion Module:

The spatial (C) and temporal (T) feature maps are not simply concatenated. This is the critical enhancement over LR's linear z.

3. Logistic Regression Head:

The context vector z_deep is passed through a final linear layer with minimal width (to preserve the link to traditional LR). This is identical in form to LR, but z_deep is a non-linear, data-driven transformation of the original inputs, rather than the inputs themselves. Training uses binary cross-entropy loss, ensuring probability calibration.

2.3 Training and Benchmarking

- **Training:** The model is trained end-to-end using the Adam optimizer. To prevent the deep backbone from overpowering the logistic head and losing calibration, a **custom loss function** combining binary cross-entropy with a penalty for excessive deviation from the expected log-odds distribution of a well-calibrated model is used.
- **Benchmark Models:**

Musik in Bayern
ISSN: 0937-583x Volume 90, Issue 12 (Dec -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-525

- **Baseline 1:** Traditional Logistic Regression on hand-engineered features (e.g., spatial averages, gradients).
- **Baseline 2:** A "Black-Box" Deep Classifier (e.g., a 3D-CNN or a pure Transformer) with a standard softmax output layer.
- **Baseline 3:** Gradient Boosting (XGBoost) as a strong non-linear benchmark.

- **Evaluation Metrics:**
  - **Discrimination:** F1-Score, Area Under the ROC Curve (AUC).
  - **Probabilistic Calibration:** Brier Score, Brier Skill Score (BSS), Reliability Diagrams.
  - **Interpretability:** Qualitative analysis of attention maps for case studies.

3. Results and Discussion

3.1 Quantitative Performance
HybridLogiNet achieves superior discrimination and calibration.

Table 1: 24-Hour Thunderstorm Forecast Performance (Global Test Set)

Model	**F1-Score**	**AUC**	**Brier Score**	**Brier Skill Score**
Logistic Regression (Engineered Feats)	0.71	0.85	0.152	0.00 (Reference)
XGBoost	0.82	0.92	0.124	0.18
3D-CNN (Black-Box)	0.89	0.95	0.098	0.36
HybridLogiNet (Ours)	**0.91**	**0.96**	**0.088**	**0.42**

The higher BSS indicates HybridLogiNet provides the largest improvement in probabilistic accuracy over the LR baseline. The reliability diagram confirms its probabilities are better calibrated than the 3D-CNN, which tends to be overconfident.

3.2 Interpretability and Case Study Analysis

The Cross-Attention Module provides the key to interpretability. For a specific thunderstorm prediction over Central Europe, we can visualize which spatial regions and past time steps received high attention weights.

- **Finding:** The model attended strongly to a plume of high 850hPa specific humidity over the Bay of Biscay at t-48h, and to a region of decreasing surface pressure over the Alps at t-12h. This aligns perfectly with a forecaster's conceptual model of moisture advection followed by orographically-forced lift.
- **Logit Weights Analysis:** While the deep features are complex, the final logistic layer's weights (W_logit) can indicate which *type* of deep feature (e.g., features representing instability vs.

ISSN: 0937-583x Volume 90, Issue 12 (Dec -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-525

features representing wind shear) was most influential for the final probability shift. This offers a higher-level explanation than analyzing millions of CNN filter weights.

3.3 Discussion: The Hybrid Advantage and Its Limits

Advantages:

1. **Performance & Calibration Synergy:** HybridLogiNet successfully marries the discriminative power of deep learning with the statistical rigor of logistic regression, achieving state-of-the-art accuracy *with* trustworthy probabilities. This is crucial for decision-making under uncertainty.

2. **Inherent Interpretability Pathways:** The architecture has explainability designed into its workflow—via attention maps and logistic weight analysis—rather than bolted on as a post-hoc analysis. This builds forecaster trust.

3. **Bridging the Paradigm Gap:** It provides a natural upgrade path for operational centers already using LR-based MOS, allowing them to incorporate modern deep learning without completely abandoning a trusted, interpretable framework.

Limitations and Challenges:

1. **Complexity vs. Simplicity Trade-off:** The model is undoubtedly more complex than LR. The "interpretability" it offers is of a different, more visual and feature-based nature than the straightforward coefficient analysis of LR.

2. **Data Hunger and Training Cost:** Like all deep models, it requires large amounts of high-quality, labeled data and significant computational resources for training, though inference is relatively cheap.

3. **Physical Consistency:** While it learns empirical patterns, it is not constrained by physical laws. There is no guarantee that its predictions are physically consistent in edge cases, unlike a NWP model.

4. **Causality vs. Correlation:** The attention maps show *associated* features, not necessarily *causal* drivers. Expert meteorological knowledge is still required to correctly interpret the model's explanations.

4. Conclusion and Future Work

This research has presented HybridLogiNet, a novel deep learning framework that re-imagines the classic logistic regression algorithm for the modern age of big data in meteorology. By using a deep spatiotemporal attention network as an adaptive, non-linear feature engine for a final logistic classification layer, we create a hybrid model that definitively outperforms both its traditional ancestor and contemporary black-box deep classifiers on the task of extreme weather prediction. Crucially, it does so while preserving the calibrated probabilistic outputs and pathways to interpretability that are non-negotiable in operational forecasting environments. This work validates the core thesis that deep learning's greatest impact in applied sciences may come not from wholesale replacement, but from the strategic augmentation of established, trusted methodologies.

Future Work:

- Operational Deployment and Human-in-the-Loop Evaluation: The most critical next step is integrating HybridLogiNet into a live forecasting workstation for a rigorous human-in-the-loop evaluation. Measuring how its probabilistic forecasts and attention visualizations actually impact forecaster confidence, decision speed, and accuracy is essential.

- Uncertainty Quantification Enhancement: Extending the model to output prediction intervals for its probabilities, perhaps via a Bayesian neural network approach for the deep backbone or by modeling the variance of z_deep.
- Multi-Task and Cascaded Forecasting: Training a single HybridLogiNet backbone to predict multiple event types (wind, rain, lightning) simultaneously, leveraging shared feature representations. Furthermore, the model could be used in a cascade, where its classification triggers a higher-resolution, localized DL model for detailed impact forecasting.
- Integration with NWP Ensembles: Using HybridLogiNet as a sophisticated post-processor for ensemble NWP systems. The deep feature extractor could learn to interpret the spread and patterns across 50+ ensemble members, directly translating ensemble information into a superior calibrated probability—a "deep learning MOS" for ensembles.
- Causal Discovery Integration: Incorporating techniques from causal discovery to constrain or regularize the attention mechanisms, pushing the model from identifying correlations towards suggesting more causally plausible drivers, further enhancing its explanatory value.

In conclusion, HybridLogiNet represents a meaningful step toward reconciling the power of artificial intelligence with the practical demands of scientific and operational meteorology. By designing models that are not just predictors but intelligent assistants, we can empower forecasters to better understand and communicate weather risks, ultimately building greater societal resilience to an increasingly volatile climate.

References:

1. Sattari, A., Foroumandi, E., Gavahi, K., & Moradkhani, H. (2025). A probabilistic machine learning framework for daily extreme events forecasting. *Expert Systems with Applications*, *265*, 126004.
2. Wan, C., Xu, Z., Pinson, P., Dong, Z. Y., & Wong, K. P. (2013). Probabilistic forecasting of wind power generation using extreme learning machine. *IEEE Transactions on Power Systems*, *29*(3), 1033-1044.
3. Lalaurette, F. (2003). Early detection of abnormal weather conditions using a probabilistic extreme forecast index. *Quarterly Journal of the Royal Meteorological Society: A journal of the atmospheric sciences, applied meteorology and physical oceanography*, *129*(594), 3037-3057.
4. Karstens, C. D., Stumpf, G., Ling, C., Hua, L., Kingfield, D., Smith, T. M., ... & Rothfusz, L. P. (2015). Evaluation of a probabilistic forecasting methodology for severe convective weather in the 2014 hazardous weather testbed. *Weather and Forecasting*, *30*(6), 1551-1570.
5. Hill, A. J., Schumacher, R. S., & Jirak, I. L. (2023). A new paradigm for medium-range severe weather forecasts: Probabilistic random forest–based predictions. *Weather and Forecasting*, *38*(2), 251-272.
6. Zhang, B., Tang, L., & Roemer, M. (2017). Probabilistic planning and risk evaluation based on ensemble weather forecasting. *IEEE Transactions on Automation Science and Engineering*, *15*(2), 556-566.
7. Loken, E. D., Clark, A. J., & Karstens, C. D. (2020). Generating probabilistic next-day severe weather forecasts from convection-allowing ensembles using random forests. *Weather and Forecasting*, *35*(4), 1605-1631.
8. Haupt, S. E., Casado, M. G., Davidson, M., Dobschinski, J., Du, P., Lange, M., ... & Zack, J. (2019). The use of probabilistic forecasts: Applying them in theory and practice. *IEEE Power and Energy Magazine*, *17*(6), 46-57.

9. Kriesche, B., Hess, R., Reichert, B. K., & Schmidt, V. (2015). A probabilistic approach to the prediction of area weather events, applied to precipitation. *Spatial Statistics*, *12*, 15-30.
10. Chen, X., Gupta, L., & Tragoudas, S. (2022). Improving the forecasting and classification of extreme events in imbalanced time series through block resampling in the joint predictor-forecast space. *IEEE Access*, *10*, 121048-121079.