International Journal of Advances in Scientific Research and Engineering (ijasre)

E-ISSN : 2454-8006

DOI: 10.31695/IJASRE.2025.10.4

Volume 11, Issue 10
October- 2025

Misclassification-Aware Hybrid Model for Binary Rainfall Prediction

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ABSTRACT

Hybrid framework for rainfall classification that integrates machine learning (ML) and deep neural network (DNN) applied on meteorological data. The primary DNN serves as robust baseline trained with normalized meteorological features from different sites in the target area after simple preprocessing such as dropping unnecessary features, using MinMaxScaler for feature scaling. To further reduce misclassification samples, a correction mechanism was applied using secondary Light Gradient Boosting Machine (LightGBM) model, which was trained only on misclassified samples by the DNN model.

ROC curve (AUC = 0.98), confusion matrix and precision recall curve proved the model differentiation ability. Furthermore, KMeans clustering highlighted the class strong separation for rain / no-rain classes. Learning curves suggested stable training optimization with consistent generation.

This hybrid method achieved overall accuracy of 98%, while both precision and F1-score were 98% with 96% recall.

As the results proves that using DNN and second ML model specifically for the misclassified samples can boost the rainfall prediction model.

Key Words: Hybrid Model, Deep Learning Neural Network, Machine Learning, Meteorological Data, Rainfall Prediction.

1. INTRODUCTION

Accurate Weather prediction needs trustworthy weather forecasting, because unpredictable weather changes such as tropical cyclones can have disastrous impacts, that makes them hard to predict correctly [1].

Numerical weather prediction (NWP) models have been used for many years for weather forecasting process, but they are computational expensive and time consuming in compared to ML which has wide range of ensemble size and lower computation cost [2].

Compared with traditional physics-based techniques, modern ML techniques suggest useful alternatives. ML models can directly learn complex patterns from meteorological data, eradicating the need for explicit physical modelling. It is also much easier to forecast rain, temperature, wind and so on in these ways. Simply because these techniques can manage high-dimensional, noisy and nonlinear data. And in addition, when the model has been trained, data output is provided quickly by the system-as needed for a resource-poor operational environment [3].

Deep learning (DL) is a subset of ML, which has incredible results in sequential data such as weather time series. Neural networks (NNs) and hybrid models are being used increasingly in storm tracking and weather prediction [4].

Long Short-Term Memory (LSTM)-based deep learning approaches have been shown to outperform traditional conceptual hydrological models across U.S. River basins, as reported in Hydrology and Earth System Sciences. The analysis emphasizes that deep networks capture temporal complexity in a way similar the proposed NN models spatiotemporal rainfall patterns [5].

Rainfall prediction is still one of the biggest issues in weather forecasting because it changes unpredictably both in time and space. In addition, the effects of microclimates, complex terrain and sparse measurement stations all contribute to a certain amount of noise surrounding predictions. This makes accurate rainfall classification difficult, as small changes in atmospheric conditions can lead unpredictable rainfall events. To overcome these sudden challenges, robust modelling methods are required [6].

Hybrid is the combination of DL with classical ML algorithms have attracted some attention in rainfall forecasting research. Such instance of this approach was the stacked hybrid model that used Bi-directional Long Short-Term Memory (BI-LSTM) and LSTM layers to improve short-term precipitation prediction accuracy. It also lifted robustness across drought-sensitive regions [7].

ML models have demonstrated strong potential in rainfall forecasting by capturing nonlinear patterns and handling noisy meteorological data. A comparative study evaluating algorithms such as Categorical Boosting (CatBoost), Extreme Gradient Boosting (XGBoost), Light GBM, Random Forest (RF), and Multilayer Perceptron (MLP) reported that ensemble and boosting methods consistently achieved higher accuracy in both daily and weekly forecasts [8]. These results stress the practical benefits of hybrid and ensemble approaches in improving reliability and robustness of rainfall prediction.

For enhancing predictive performance, feature selection is just as important as model architecture improvements from both hybrid methods and ensembles. In order to improve model-accuracy, reduce computational costs, and enhance interpretability in high-dimensional datasets feature selection plays a critical role. Hybrid swarm intelligence algorithms like Particle Swarm Optimization (PSO) combined with Genetic Algorithms (GA), or Ant Colony Optimization (ACO) are increasingly used to balance exploration and exploitation within the search space. These hybrid meta-heuristics have shown superior performance over standalone methods, especially in complex optimization tasks making them a promising tool for data-driven prediction problems with large sets of features that are noisy and nonlinear [9].

Not only Artificial intelligence (AI) is used in rainfall prediction, but also in many domains such as network traffic classification to enhance Quality if Service (QoS) [10], healthcare, automotive, airspace, robotics, mining and additional application areas [11].

2. RELATED WORK

Avula et al. investigated the application of ML models, such as artificial neural networks (ANNs), radio frequency (RF), and K-Nearest Neighbors (KNN), for the classification of heavy rain using meteorological data derived from satellites. According to the research's findings, the ANN model had the greatest accuracy 95.6% and the RF 86.1%, while the KNN model only had a 79.7% accuracy rate. According to the study, machine learning approaches have the potential to greatly enhance the forecast performance for extreme weather occurrences, particularly in situations when traditional observation networks can be limited or unavailable [12].

Hasan et al. evaluated historical meteorological data and examined a number of machine learning (ML) techniques to forecast when it would rain, including Decision Tree (DT), Naïve Bayes (NB), RF, Support Vector Machine (SVM), LSTM, Logistic Regression (LR), and ANN. With an accuracy rate of up to 91%, the ANN outperformed the other models. This offers convincing proof that its application can capture rainfall distributions that are not linear. The promise of ANN-based binary rain prediction approaches is highlighted by this work, particularly those that use combined characteristics from various meteorological circumstances [13].

Ria et al. examined rainfall prediction using different ML algorithms, such as DT, KNN, LR, Multinomial Naïve Bayes (MBN), and RF, applied to Bangladesh daily climate dataset ranging from 2016 to 2019. The dataset contains features such as temperature, humidity, sunshine, and solar radiation. Between the tested models, RF achieved the highest classification accuracy of 87.68%, precision of 90.63%, recall of 92.46%, and F1-score of 91.54%, surpassing all other models [14].

Hudnurkar and Rayavarapu proposed a binary classification approach for summer monsoon rainfall prediction using SVM and ANN. The study utilized nineteen years of daily weather data temperature, humidity, and pressure from Shivajinagar station in Maharashtra, India, labelling days as “rainy” or “non-rainy” based on a 2.5 mm threshold. The ANN model achieved slightly better F1-score and misclassification rate than polynomial-kernel SVM, with both attaining around 82% accuracy on the primary dataset. Domain adaptation tests on other stations showed reduced accuracy, but performance improved significantly when training data was augmented with local station records [15].

Raval et al. proposed an automated predictive analytics tool for rainfall forecasting that incorporates multiple ML algorithms into a comparative evaluation framework. Historical meteorological data from the Australian Bureau of

DOI: 10.31695/IJASRE.2025.10.4

Meteorology were pre-processed, subjected to feature selection, and classified using models including LR, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), KNN, DT, Gradient Boosted Trees (GBT), RF, Bernoulli Naïve Bayes (BNB), and a DL neural network. Among the statistical models, LR achieved the highest F1-score of 86.87% and a precision of 97.14%, while the DL model outperformed all tested approaches, attaining an F1-score of 88.61% and a precision of 98.26%. This shows the power of DL in comparison to the ML models in mastering complex and nonlinear rainfall patterns [16].

Asim et al. compared LR, DT, RF, and ANN models for next-day rainfall prediction using data from 49 Australian weather stations (145,460 instances). The authors reported that the RF model achieved the highest accuracy of 85.55% among the models considered, with a precision of 75.28% and a well-balanced F1-score of 56.11% [17].

Elkenawy et al. proposed a voting ensemble framework combining RF and XGBoost, with voting weights optimized using the Adaptive Dynamic Puma Optimizer (AD-PO) and the Guided Whale Optimization Algorithm (Guided WOA). The objective was to enhance the robustness of rainfall classification and forecasting by addressing nonlinear patterns and climate variability. This approach achieved an overall accuracy of 95.99%, with a precision of 94.47 and an F1-score of 97.30 [18].

Saeed Khan et al. applies LR for daily rain prediction in Aligarh, India, using humidity, temperature, and cloud cover. The reported precision is 81.22%, recall 79.40%, and F1-score 80.30% [19].

3. METHODOLOGY

3.1 Study Area and Dataset

The experiments in this study utilized the Maastricht subset of the publicly available Weather Prediction Dataset [20], originally compiled by Huber et al. (2021) and partly based on daily observations from the European Climate Assessment & Dataset (ECA&D) project [21]. The original dataset contains weather measurements from 18 European stations; however, only the Maastricht station data, consisting of 3,654 daily instances, was extracted for model development to maintain spatial consistency. Daily measurements include variables such as temperature (mean, min, max), humidity, cloud cover, wind speed and gust, global radiation, and sunshine duration. To prevent data leakage and temporal bias during model training, the original precipitation values and DATE columns were excluded from the feature set. A binary classification target was constructed by labelling all precipitation values greater than zero as rain (class 1) and zero as no rain (class 0).

3.2 Data Preprocessing

All numerical features were normalized to the range [0, 1] using the MinMaxScaler to scale feature magnitudes for NN training. To address the moderate class imbalance in the dataset, stratified sampling was employed to preserve the rain/no-rain ratio across all partitions. The dataset was divided into training (60%), validation (15%), and test (25%) subsets, ensuring both statistical consistency and robust model evaluation.

3.3 Primary Model: Deep Neural Network

A feedforward DNN was implemented using the TensorFlow/Keras framework, with an input layer matching the number of features, followed by two hidden layers of 64 and 32 neurons respectively, each using the ReLU activation function. The output layer consisted of a single neuron with sigmoid activation to produce rain/no-rain probabilities.

The model was compiled with the Adam optimizer and binary cross-entropy loss and trained for 30 epochs with a batch size of 32, using the validation set for monitoring. Learning curves tracking accuracy and loss were monitored to ensure stable training and detect potential overfitting or underfitting.

3.4 Error Correction with LightGBM

The DNN was first trained on the full training set to serve as the primary classifier. Following this initial training, predictions were generated for the validation set, and misclassified samples were identified. These validation misclassifications formed the training data for a secondary LightGBM classifier, which learned patterns specific to these difficult to classify cases.

During inference on the test set, the DNN predictions were computed first. Any test samples misclassified by the DNN were then passed through the LightGBM model, whose predictions selectively replaced the original outputs. This two-stage "misclassification-aware" correction was designed to capture residual decision boundaries that the DNN failed to model effectively.

DOI: 10.31695/IJASRE.2025.10.4

3.5 Hybrid Rain Classifier Algorithm

INPUT:
  Dataset $\mathrm{D} = \{\mathrm{X}, \mathrm{p}\}$ where p is precipitation and X represents the remaining meteorological features
OUTPUT:
  Predictive model M for rain occurrence
BEGIN
1. Create binary target:
   $y \leftarrow 1$ if $p > 0$ else 0
   Remove p and date from X
2. Split D into $(\mathrm{X\_train}, \mathrm{y\_train})$, $(\mathrm{X\_val}, \mathrm{y\_val})$, $(\mathrm{X\_test}, \mathrm{y\_test})$ stratified
3. Normalize features:
   Apply MinMaxScaler using training set
4. Initialize primary model M_1 (NN)
5. Train M_1:
   FOR epoch = 1 to E DO
     Update weights on (X_train, y_train)
     Validate on (X_val, y_val)
   END FOR
6. Evaluate M_1on test set → predictions $\hat{y}\_test$
7. Identify misclassified validation samples:
$$\mathrm{V_{mis}} = \{(x, y) \epsilon\ (\mathrm{X\_val}, \mathrm{y\_val}) | M_1(x) \neq y\}$$

8. Train secondary model M_2 (LightGBM) on V_mis
9. Correct test predictions:
   For each misclassified x in X_test:
     $\hat{\mathrm{y}}\_\mathrm{test}[x] \leftarrow M_2(x)$
10. Evaluate final corrected predictions
END

4. RESULTS

The primary NN model, trained with binary cross-entropy loss, initially achieved an accuracy of 82% on the test set, with a precision of 0.88 for no-rain (class 0) and a recall of 0.91 for rain (class 1). Despite these promising results, the model produced 163 misclassifications, indicating room for further refinement, especially for ambiguous weather instances.

To address these errors, a secondary LightGBM model was trained exclusively on the misclassified validation samples as a targeted correction step rather than full retraining. Applying this selective correction dramatically improved the model's performance.

The final hybrid DL-LightGBM model reached an impressive accuracy of 98% on 914 test samples, with only 19 misclassifications remaining. Class 0 was predicted with a near-perfect recall of 1.00, while class 1 achieved a recall of 0.96, culminating in a weighted F1-score of 0.98. This substantial performance gain validates the effectiveness of combining a primary DL classifier with a misclassification aware boosting approach.

Evaluation used several complementary metrics and visualization methods to provide a comprehensive performance assessment. Roc and precision recall curves proved the model's strong discriminative ability and resilience to class imbalance. The confusion matrix showed a balanced classification between rain and no-rain cases, while KMeans clustering on PCA reduced features revealed clear natural groupings aligned with the binary labels.

Finally, learning curves from the DNN training phase demonstrated smooth convergence without signs of overfitting, supporting its task as a stable foundation for the secondary model.

This improvement highlights the benefit of training a secondary model dedicated on difficult samples, effectively improving the decision boundaries of the primary classifier and confirming the core hypothesis of this study targeted correction of misclassified outputs enhances binary rainfall prediction accuracy.

DOI: 10.31695/IJASRE.2025.10.4

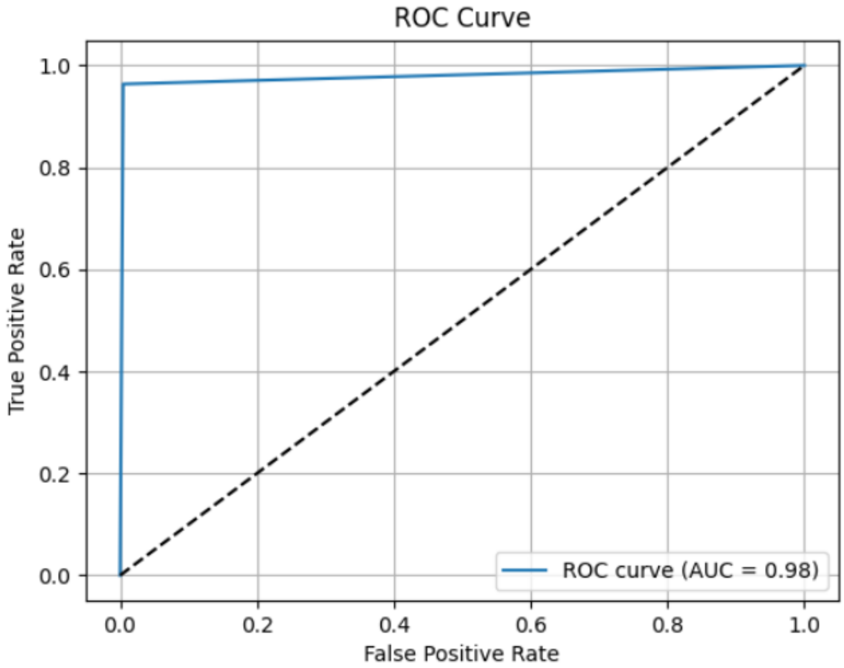

Figure 1. ROC curve

(Figure 1) displays the ROC curve of the hybrid model, illustrating high discrimination between rain and no-rain classes with an area under the curve (AUC) of 0.98. The curve's steep ascent and low false positive rate indicate the model's robustness across diverse meteorological conditions.

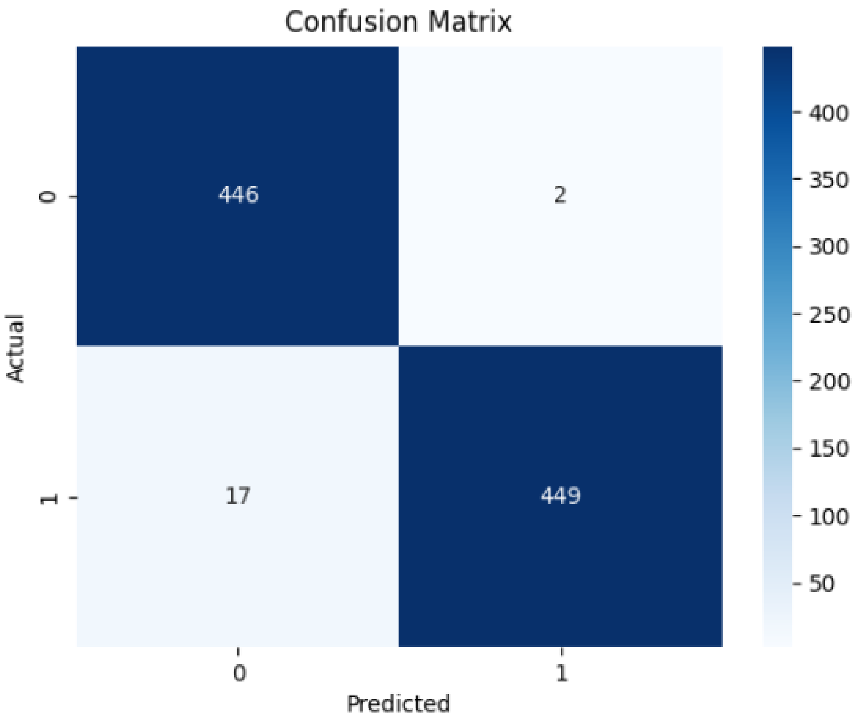

Figure 2. Confusion matrix.

DOI: 10.31695/IJASRE.2025.10.4

The confusion matrix in (Figure 2) further illustrates the balanced performance, with 446 out of 448 no-rain samples and 449 out of 466 rain samples correctly classified. This balance minimizes both false positives and false negatives, which is critical for reliable weather forecasting.

Figure 3. KMeans clustering of PCA-reduced test data.

A KMeans clustering analysis following PCA dimensionality reduction on the test set (Figure 3) reveals two well-separated clusters that correspond closely to the binary rain/no-rain labels. This clustering visually confirms the meaningful meteorological structures learned by the model despite the unsupervised nature of the clustering step.

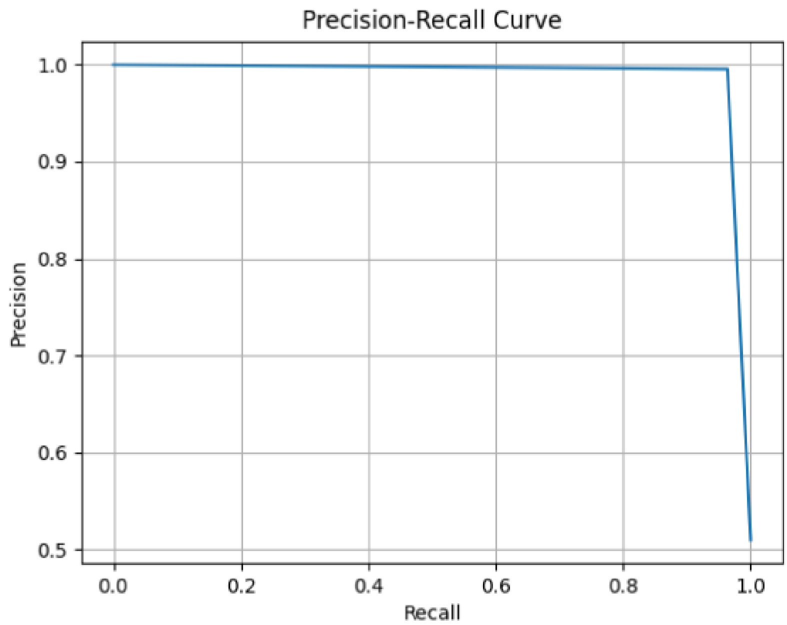

Figure 4. Precision-Recall curve.

DOI: 10.31695/IJASRE.2025.10.4

The Precision-Recall curve (Figure 4) displays consistently high precision above 0.95 across a wide range of recall values, highlighting the model's resilience to class imbalance and threshold variation.

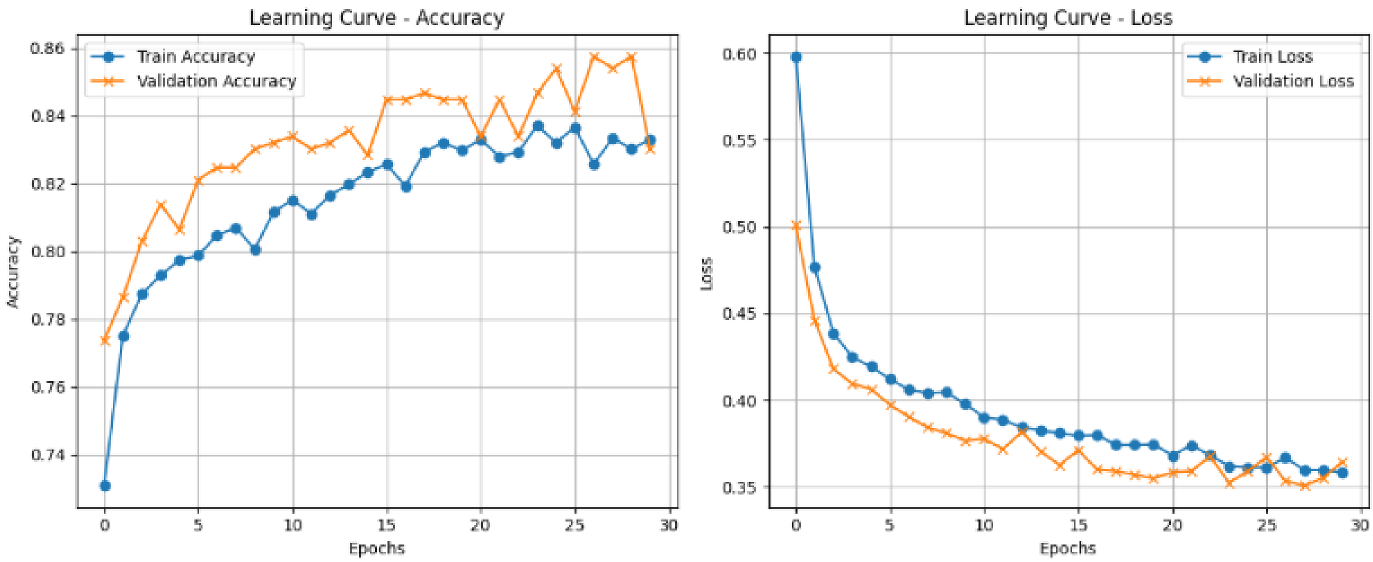

Figure 5. Learning curves.

Finally, the learning curves (Figure 5) illustrate smooth convergence of accuracy and loss during training over 30 epochs, with no signs of overfitting. These stable dynamics support the use of the primary NN as a robust foundation for the secondary correction by LightGBM.

5. DISCUSSION

The comparison in Table 1 highlights the range of methods applied to rainfall prediction, with accuracies typically between 70% and 96% across studies using ANN, RF, SVM, and ensemble models. Many previous works achieved good results but often lacked mechanisms to specifically address misclassifications.

The hybrid model combining a deep learning DNN with a secondary LightGBM correction shows a clear improvement, reaching 98% accuracy with balanced precision and recall 98% and 96%, respectively. This suggests that targeted correction of misclassified samples effectively refines model predictions beyond what single models typically achieve.

Table 1. Comparison of Rainfall Prediction Models

Ref	Methods	Best Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
[12]	ANN, RF, KNN	ANN	95.6	—	—	—
[13]	DT, NB, RF, ANN, SVM, LSTM, LR	ANN	91	88	89	89
[14]	DT, KNN, LR, NB, RF	RF	87.68	90.63	92.46	91.54
[15]	SVM, ANN	ANN	82.8	0.761	—	0.711
[16]	LR, LDA, QDA, KNN, DT, Gradient Boosting, RF, BNB, DL	DL		98.26	—	88.61
[17]	LR, DT, RF, ANN	RF	85.55	75.28	—	56.11
[18]	Voting ensemble combining RF and XGBoost, with voting weights optimized using AD-PO integrated with Guided Whale Optimization Algorithm (Guided WOA)	AD-PO-Guided WOA voting ensemble	95.99	94.47	—	97.30
[19]	LR, DT, RF, MLP	LR	82.80	81.22	79.40	80.30
Proposed Model	Hybrid DL (NN) + ML (LightGBM)	Hybrid model	98.0	98.0	96.0	98.0

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6. CONCLUSION

The study's findings demonstrated that integrating deep learning with secondary machine learning correction enhances rainfall forecasts. The way this combined strategy works is by utilizing each method's unique strengths: A main neural network serves as the first classifier, and a second corrector then handles ambiguous predictions. The method lowers the frequent misclassification mistakes that afflict weather forecasting work and improves model reliability overall. This method is appropriate for practical use in meteorology due to its great training efficiency and universality.

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