HI²NN: Heuristic Intelligence towards Enhancing Rainfall Prediction with Improved Artificial Neural Networks

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Abstract

Predicting rainfall proves critical for businesses to organize their water resources, make agricultural choices, and prevent disasters. Therefore, proposed model presents a novel approach, namely Heuristic Intelligence towards Enhancing Rainfall Prediction with Artificial Neural Networks (HI²NN) to enhance rainfall prediction by designing heuristic Intelligence combined with Improved Artificial Neural Networks (IANNs). The proposed HI²NN framework leverages heuristic optimization techniques to fine-tune ANN parameters to improve prediction accuracy. Prediction accuracy is computed through our designed custom accuracy metric. The methodology uses historical weather information to extract complex non-linear patterns, which neural models generate from the designed big dataset. The accuracy level of rainfall predictions using our methodology achieves 92%, which demonstrates superior performance than traditional approaches that include random forest and decision tree and XGBoost models. The new forecasting systems develop higher reliability through collaborative efforts between heuristic algorithms and neural networks as described in this research work targeting challenging meteorological forecasts.

Keywords: Correlation; Meteorological Data; Machine Learning; Deep Learning; Rainfall; Prediction; Heuristics

1. Introduction

The accurate prediction of rainfall stands essential for meteorology because it affects agriculture production together with urban development planning and water resource planning and natural disaster prevention. Weather predictions support farmers to schedule plantings effectively while municipalities require them for managing water distribution and governments need them to prepare for severe weather events. The critical situation demanding better and more dependable forecasting methods stems from rising weather pattern unpredictability caused by climate change. The traditional rainfall prediction techniques described in papers [5] and [6] struggle to identify hidden non-linear relationships that exist in meteorological data. The systematic approach falls short of properly identifying and quantifying various precipitation-influencing elements including temperature along with humidity and wind conditions together with land characteristics. The application of Artificial Neural Networks as part of machine learning techniques has extended possibilities to improve rainfall forecasting during recent years [7, 8]. ANNs perform efficiently with large datasets and complex pattern recognition capabilities, which makes them qualified candidates for the current task. The implementation of ANNs for rainfall prediction depends heavily on both their design structure and parameter adjustments but faces difficulties in proper implementation. Natural and human-based problem-solving approaches inspire heuristic optimization techniques as a promising solution to handle this challenge. The predictive power of ANNs together with their adaptability becomes stronger when heuristic optimization explores the network parameters and optimizes structural elements. A new framework has been established to combine heuristic intelligence methods with ANNs for enhancing rainfall prediction accuracy. The proposed approach integrates weather data from the past together with heuristic algorithms for optimizing ANN configurations, which produces forecasts of higher accuracy. Our research explored theoretical aspects regarding this integration while describing our methodology and presenting results that proved the effectiveness

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of our approach. Our research aims to help the development of rainfall prediction methods, which will aid better choices across all sectors that require accurate weather prediction.

1.1 Motivation

Development of HI^{2}NN framework emerges because rain prediction requires more precise and reliable techniques. The changing global weather patterns because of climate change have increased the challenge for meteorological models to generate prompt and accurate predictions [5; 6]. Unforeseen weather patterns produce major effects, which contribute to agricultural damages and shortage of water supplies and heightened exposure to natural disasters.

Interesting forecasting approaches from research papers [5 and 6] depend upon linear modeling systems, which fail to represent the sophisticated patterns inside atmospheric information. ANNs together with ML represent breakthrough possibilities because their capacity to extract knowledge from big data sets enables them to detect non-trivial associations in the data. ANNs have not reached their maximum potential because technical problems exist when optimizing network parameters and structures for distinct forecasting applications.

The challenge gets resolved through heuristic optimization techniques that conduct purposeful examinations and enhancements of ANN configurations. Heuristic intelligence improves the prediction process of rainfall by enhancing the model's performance for accurate adaptation to climate changes. By integrating heuristic optimization techniques, the prediction accuracy will increase while researchers gain better comprehension of meteorological events at work.

Because of this, HI^{2}NN is developed to provide the decision makers in various sectors (e.g. in agriculture, water management, or disaster response) with the needed reliable tools for predicting the rainfall patterns. We seek to reduce the impact of climate variability on governance of the ecosystem and to promote more sustainable resource management through a more effective forecasting practice.

1.2 Contribution

a) **Designed Big Dataset:** The study created a big database, which covered multiple years to show rainfall pattern diversity so that HI^{2}NN framework delivered superior rainfall prediction results.

b) **Enhanced Prediction Accuracy:** By applying heuristic optimization to ANNs HI^{2}NN aims to enhance both model structure selection along with parameter adjustment in order to achieve better prediction accuracy. HI^{2}NN achieves higher accuracy in rainfall predictions than traditional methods and basic ANN approaches because of its system design.

c) **Adaptability**: Based on its heuristic intelligence design HI^{2}NN functions to detect complex non-linear data patterns, which exist in meteorological data. The adaptable nature of the model generates better reliable forecasts under conditions of climate change.

d) **Robust Framework:** For The proposed HI^{2}NN framework builds a structured approach for heuristic optimization integration with ANNs to perform forecasting. The structure enables the development of correct forecasting models while providing essential guidance for additional meteorological research projects.

The HI^{2}NN framework has advanced rainfall prediction technology by offering theoretical improvements as well as operational benefits to improve weather-dependent decision-making in different impacted sectors.

2. Related Work

Prediction of rainfall stands as a vital meteorological concept that benefits agricultural planning [1] and controls water resources management [3] and serves disaster prevention [4]. Statistical approaches including ARIMA and linear regression lack effectiveness when used to analyze the non-linear chaotic characteristics of weather systems according to research [9] [10]. ANNs emerged because they identify complex nonlinear relationships between data points with excellence. Researchers in [7, 11] and [29] have proven through their work that ANNs with MLP structures surpass traditional statistical approaches in complex model approximations.

The combination of heuristic intelligence techniques comprises Genetic Algorithms (GA) [12] together with Particle Swarm Optimization (PSO) [13] and Ant Colony Optimization (ACO) [14] that enhances ANN architectural optimization. The procedures enable better features to be selected while optimizing hyperactive parameters that enhances prediction accuracy along with computational speed. The optimization techniques involved several negative side effects, which researchers encountered when implementing them:

a) Computational Complexity: Evaluation through optimization methods becomes harder because they need substantial computational power and extended processing time when working with extensive datasets. Training times increase as well as processing costs due to calculations being magnified by these methods [15].

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b) Parameter Sensitivity: These optimization algorithms demonstrate sensitiveness to their control parameters, which affects their overall performance. The incorrect setting of parameters creates poor results that diminishes the process quality and complicates its replication attempts [16].

c) Local Optima: this optimization methods show restricted effectiveness because they reach suboptimal solutions instead of global optimal solutions [17]. The models fail to reach their maximum optimal performance level when searching complex optimization spaces.

d) Overfitting Risk: The risk of overfitting occurs in ANN architecture optimization when exploration exceeds acceptable limits or when validation methods fail to be robust. The model develops reduced performance on unknown data when this situation occurs [18].

e) Interpretability Issue: These optimization methods create complex models which reduces their interpretability features according to studies found in [19, 20].

f) Dependency of Quality of Initial Solution: The GA and PSO need high-quality initial solutions or population to function properly [21]. The quality of initial configurations determines whether optimization succeeds and how effectively models will be configured after initialization [22].

g) Scalability Challenges: As the dataset's size and the model's complexity increase, the scalability of these optimization techniques can become a concern, potentially leading to diminishing returns in performance improvements [23, 24].

Therefore, to eliminate these drawbacks, this study has shown that hybrid models combining the improved ANNs with the designed heuristic approaches can enhance predictive capabilities by effectively addressing overfitting issues and model convergence.

3. Proposed System Architecture

The proposed HI^{2}NN framework has its system architecture presented in Figure 1

Functionality within the HI^{2}NN framework relies on various essential parts that optimize rainfall prediction performance. The architecture has three distinct operational layers, which can be separated as follows:

- **Data Acquisition Layer:**
- **Input Data Sources:** This layer collects the required data from the designed big dataset as described in Section 5.
- **Data Preprocessing:** Clean-up processes are applied to raw data while normalization procedures normalize inconsistent data then transform it to remove generated noise. Missing values are handled through interpolation or other imputation techniques.
- **Feature Extraction Layer:**
- **Feature Selection:** Relevant features are identified through statistical analysis and ML techniques. By decreasing, the number of important elements and focusing on key factors that affect rainfall this approach becomes more effective.
- **Data Transformation:** Extracted features undergo transformations (e.g., scaling and encoding) to enhance the learning process of the neural network.
- **Heuristic Optimization Layer:**
- Heuristic Algorithms: Designed heuristic optimization techniques are implemented to explore and optimize the ANN architecture described in Algorithm 1.
- **Parameter Tuning:** The selected heuristic algorithm iteratively adjusts the ANN parameters to identify the optimal configuration for the rainfall prediction task as described in Table 1.

Table 1: Parameter Tuning for the Designed *HI^{2}NN* Model

Parameter	Value	Performance Metric (Custom Accuracy)
Learning Rate	0.001	Accuracy: 85%
Batch Size	32	Accuracy: 87%
Epochs	50	Accuracy: 90%
Hidden Layers	10	Accuracy: 88%

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Neurons per Layer	64	Accuracy: 91%
Activation Function	ReLU	Accuracy: 89%
Dropout Rate	0.5	Accuracy: 92%

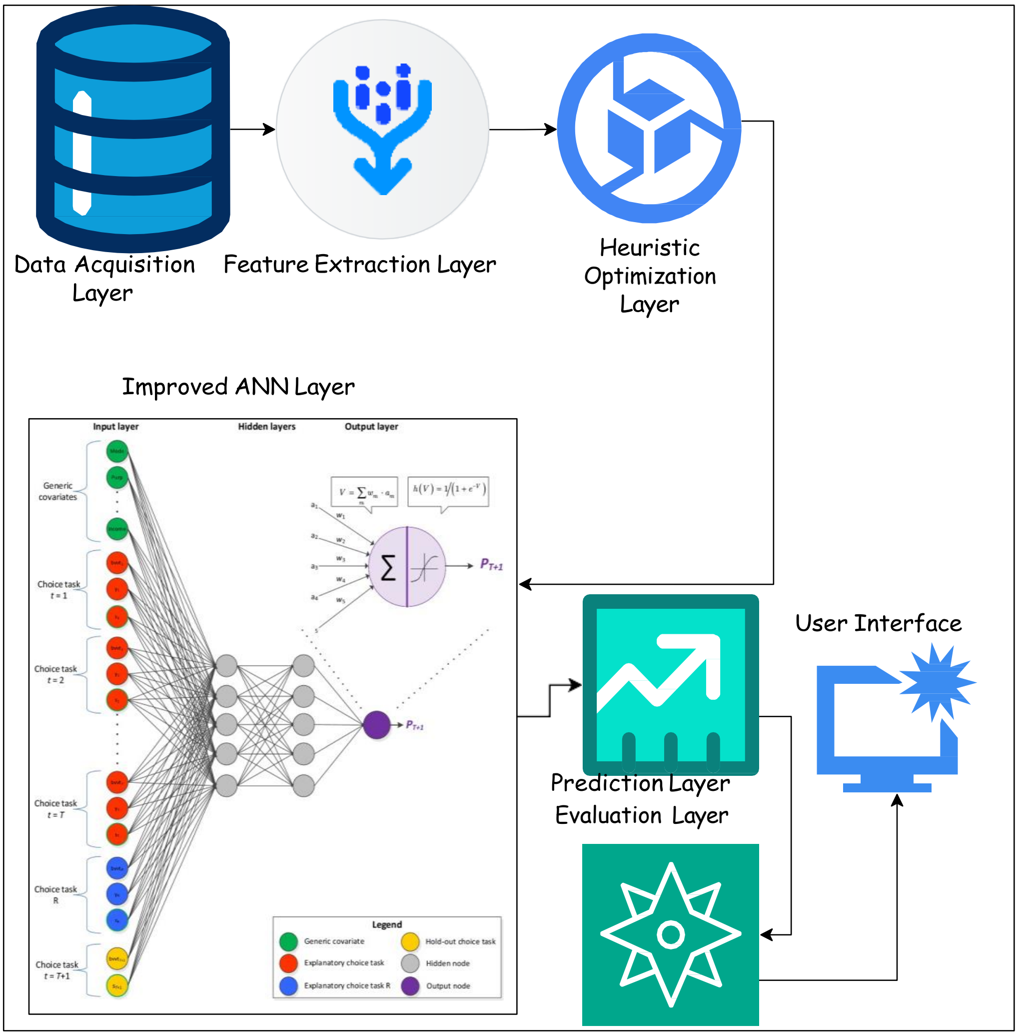

Figure 1. Proposed System Architecture of the HI^2NN Framework.

Algorithm 1 Heuristics for the Proposed HI^2NN Framework

procedure HI^2NN HEURISTIC (*data, parameters, max iterations*)
  model ← InitializeModel(*parameters*)
  best_solution ← InitializeBestSolution()
  iterations ← 0
  while *iterations* < *max_iterations* **do**
    solution ← GenerateSolution(*model, data*)
    if Evaluate(*solution*) > Evaluate(*best solution*) **then**
      best solution ← *solution*
    end if
    model ← UpdateModel(*model, solution*)
    iterations ← *iterations* + 1
  end while
  Return *best_solution*
end procedure

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- **Improved Artificial Neural Network (IANN) Layer:**
- **IANN Architecture:** A feed-forward perceptron architecture is con- structed based on the optimized parameters.
- **Training Process:** The IANN is trained using the processed data, applying backpropagation and Adam optimization techniques to minimize pre- diction errors. The HI^2NN framework is validated using cross-validation to ensure robustness.

- *Prediction Layer:*

- **Forecasting Module:** The deployed trained ANN model generates rainfall predictions based on incoming data values.

- **Output Processing:** The software generates raw predictions during a subsequent structural phase where operators obtain understandable result types such as probability distributions or categorical classifications (for instance likelihood of rainfall).

- **Evaluation Layer:**

- **Performance Metrics:** A predictive model determines its accuracy evaluation through Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Metrics along with Custom Accuracy (CA) metric values designed for this application.
- **Feedback Loop:** The collected results go through analysis for delivering feedback, which leads to ongoing model optimization through consecutive refinement cycles.

- *User Interface Layer:*

- **Visualization Dashboard:** A visualization dashboard made accessible for end-users presents rainfall predictions together with data visual elements (such as graphs and heatmaps) alongside uncertainty information to meteorologists, farmers and policy makers.

- HI^2NN utilizes a cohesive architecture with its components to provide improved rainfall predictions as well as adaptable features for big dataset and forecasting requirements. The systematic method enables the model to obtain knowledge from historical information and enhance its predictive performance with heuristic intelligence.

4. Problem Formulation

The objective of HI^2NN is to forecast rainfall quantities using previously collected weather information. The following variables need definition:

- We define the input vector as X that contains historical weather parameters.

- Y represents the predicted rainfall data within the output vector.

- The weight matrix of the neural network bears the name W.

- Let b be the bias vector.

The IANN produces results according to this formula:

$$Z = f(W \cdot X + b) \tag{1}$$

where f is the sigmoid activation function.

The heuristic approach can further refine the parameters by incorporating a heuristic function H:

$$H(W, b) = \alpha \cdot L + \beta \cdot R \tag{2}$$

The regularization term R prevents overfitting by working together with factors α and β.

The complete optimization objective boils down to:

$$\min_{W, b} H(W, b) \tag{3}$$

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5. Designed Big Dataset

A well-trained big dataset in HI^2NN framework determines how effective this model performs through the training process. Various aspects make up the designed big dataset structure to guarantee reliable and precise rainfall prediction results. This designed big dataset contains three main elements.

- *Data Sources:*

Meteorological Stations: Meteorological Stations obtain data from the Australian government website [25]. The public climate dataset known as Climate Databases supplies historical weather data which supports detailed analysis [25].

- *Temporal Scope:*

Longitudinal Data: A ten-year time span exists within the dataset to ascertain seasonal effects combined with extreme weather events together with persistent climate patterns. The extended time span helps the model detect time-based patterns that lead to improved accuracy of its predictions.

- *Feature Variables:*

Meteorological Variables: The dataset contains fundamental features, which include Temperature (daily maximum, minimum, average) and Humidity (relative humidity levels) along with Wind Speed and Direction information and Atmospheric Pressure measurements and Precipitation information including rainfall amounts and frequency as well as Evaporation data.

Additional Features: Derived features include:

(i) Lagged variables (previous days' weather conditions)

(ii) Seasonal indicators (e.g., month, season)

- *Data Quality and Preprocessing:*

a) Data Cleaning: The dataset is subjected to rigorous cleaning processes to remove inconsistencies, outliers, and missing values using interpolation and statistical imputation techniques. b) **Normalization and Scaling:** Features are normalized and scaled to ensure uniformity, allowing the improved ANN to learn effectively without biases due to differing scales of various features.

- *Labeling and Target Variable:*

(a) **Target Variable:** The primary target variable for prediction is the amount of rainfall over specified time intervals. The dataset is labeled to indicate whether rainfall occurred, the intensity of rainfall, and the duration.

- *Volume and Scalability:*

(a) **Big Data Considerations:** The designed dataset is substantial, potentially comprising millions of rows, especially when combining multiple sources and features over several years. This large volume allows for robust training of the improved ANN and enhances its predictive capabilities.

(b) **Scalable Architecture:** The dataset is structured to support scalable storage and processing solutions, such as cloud-based platforms, enabling efficient handling and analysis of big data.

Algorithm 2 presents the designed big dataset for the HI^2NN framework.

6. Designed Improved ANN & Heuristics Techniques for the Proposed HI^2NN Framework

6.1 Improved Artificial Neural Network (IANN)

The proposed IANN architecture is designed by incorporating several layers and components as described in Table 2.

This architecture consists of an input layer, multiple hidden layers, and an output layer as described in Table 3.

The forward pass computes the output of each hidden layer sequentially. For the first hidden layer, the output is calculated using the following Equation (4).

$$H_1 = f(W_1 \cdot X + b_1) \tag{4}$$

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where, W_1 represents the weights, X is the input vector, and b_1 is the bias term.

This process continues for subsequent hidden layers, with the second layer's output given by the following Equation (5).

$$H_2 = f(W_2 \cdot H_1 + b_2) \tag{5}$$

The third layer can be represented as the following Equation (6).

$$H_3 = f(W_3 \cdot H_2 + b_3) \tag{6}$$

Finally, the output layer produces the predicted value using the following Equation (7).

$$Y = \sigma(W_{out} \cdot H_3 + b_{out}) \tag{7}$$

where σ denotes the sigmoid activation function.

Table 2: Proposed Improved ANN Architecture

Layer /Components	**Description**	**Purpose**
Input Layer	Receives input features (e.g., temperature, humidity)	Initializes data for prediction
Hidden Layer 1	First hidden layer with activation function (e.g., ReLU)	Captures non-linear relationships
Hidden Layer 2	Second hidden layer with dropout regularization	Prevents overfitting
Output Layer	Single neuron output layer with activation function (e.g., Sigmoid)	Generates final rainfall prediction
Loss Function	Mean Squared Error (MSE)	Measures prediction accuracy
Optimization Algorithm	Adam optimizer	Updates weights to minimize loss
Training Epochs	Number of iterations (e.g., 1000)	Determines training duration
Learning Rate	Hyperparameter (e.g., 0.001)	Controls weight updates
Batch Size	Number of samples per update (e.g., 32)	Influences training efficiency

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Algorithm 2 Designing the Big Dataset for the Proposed HI^2NN Framework

procedure DESIGNBIGDATASET
  Input: Historical meteorological data sources, remote sensing data, climate databases
  Output: Comprehensive big dataset for HI^2NN model
  Initialize empty dataset $D \leftarrow \{\}$
  for each data source in {Meteorological Stations, Remote Sensing, Climate Databases } **do**
    Retrieve data from the source
    Clean the data:
      Remove duplicates
      Handle missing values using interpolation or imputation
      Remove outliers based on statistical analysis
    Normalize and scale features
    Append cleaned data to D
  end for
  Feature Engineering:
  for each feature in D **do**
    Identify relevant features (e.g., temperature, humidity, wind speed)
    Generate derived features (e.g., lagged variables, seasonal indicators)
  end for
  Labeling:
  for each time interval in dataset **do**
    Assign target variable (e.g., rainfall amount, occurrence)
  end for
  Return: Dataset D ready for HI^2NN model training and validation
end procedure

Table 3: The architecture of the improved ANN

Layer	Neurons	Activation Function
Input Layer	1	-
Hidden Layer 1	20	ReLU
Hidden Layer 2	20	ReLU
Hidden Layer 3	20	ReLU
Output Layer	1	Sigmoid

To evaluate the HI^2NN framework's performance during training, the Mean Squared Error (MSE) loss function is utilized, defined as follows:

$$L = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2 \tag{8}$$

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where, N is the number of samples, Y_i is the actual rainfall value, and $\hat{Y}_i$ is the predicted output.

The backpropagation algorithm updates the weights and biases using gradient descent, expressed as Equations (9), and (10).

$$W \leftarrow W - \eta \frac{\partial L}{\partial W} \quad (9)$$

$$b \leftarrow b - \eta \frac{\partial L}{\partial b} \quad (10)$$

where, η is the learning rate, ensuring that the model learns effectively from the training data.

Therefore, the improved ANN architecture, with its multi-layer structure and effective activation functions, is designed to enhance the proposed HI^2NN framework's ability to predict rainfall accurately.

6.2 Heuristics

To optimize the performance of the IANN in the context of rainfall prediction, several heuristic strategies have been identified and implemented within the HI^2NN framework. These heuristics aim to improve both the training efficiency and the predictive accuracy of the model. Key heuristics include:

- Adaptive Learning Rate

An adaptive learning rate dynamically adjusts the learning rate during the training process. One common method is the Adam optimizer, which updates the weights W as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\nabla \mathrm{L(W)} \quad (11)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)(\nabla \mathrm{L(W)})^2 \quad (12)$$

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (13)$$

$$W \leftarrow W - \eta \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (14)$$

where m_t and v_t are the first and second moments of the gradients, β_1 and β_2 are decay rates, η is the learning rate, and ϵ is a small constant to prevent division by zero.

- Early Stopping

Early stopping involves monitoring the model's performance on a validation set and halting training when performance begins to degrade. If L_{train} is the training loss and L_{val} is the validation loss, the condition for early stopping can be expressed as:

$$Stop\ if\ L_{val}^{(k)} > L_{val}^{(k-1)}\ for\ a\ defined\ patience\ period \quad (15)$$

where k is the epoch number.

- Regularization Techniques

Regularization methods, such as L_2 regularization (also known as weight decay), can be applied to the loss function to discourage complex models. The modified loss function L' can be defined as:

$$L' = L + \sum_{i=1}^{n} W_i^2 \quad (16)$$

where λ is the regularization parameter, W_i are the weights, and n is the number of parameters. This helps prevent overfitting by penalizing large weights.

- Batch Normalization

Batch normalization normalizes the output of each layer to improve con- vergence speed. The transformation for a mini-batch B can be expressed as:

$$\hat{X} = \frac{X - \mu_B}{\sqrt{\sigma_B^2 + \beta}} \quad (17)$$

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$$Y = \gamma \hat{X} + \beta \qquad (18)$$

where μ_B and σ_B^2 are the mean and variance of the batch and γ and β are learnable parameters that scale and shift the normalized output

By implementing these heuristics, we aim to significantly enhance the performance of the IANN in the *HI²NN* framework for more accurate rainfall predictions.

7. Proposed Model

The methodology proposed for the *HI²NN* framework involves a systematic integration of *heuristic techniques* with an *IANN* framework to improve the accuracy of prediction of rains. Initially, relevant heuristics are identified to guide the selection of characteristics, ensuring that the most impactful variables are used in the model. Heuristics can be used to guide the development and training of the *HI²NN* model, enhancing its efficiency and effectiveness in predicting rainfall as follows:

- *Weight Initialization Heuristic:*

$$w_i = \mathcal{N}(\mu, \sigma^2) \qquad (19)$$

where, w_i is the weight of the i^{th} neuron, denotes a normal distribution, μ is the mean, and σ^2 is the variance.

- *Feature Importance Evaluation:*

$$\boldsymbol{F_i = \frac{c_i}{\sum_{j=1}^{m} c_j} \quad for\ i = 1, 2, \ldots, m} \qquad \mathbf{(20)}$$

where, $\boldsymbol{F_i}$ is the importance of the $\boldsymbol{i^{th}}$ feature, and $\boldsymbol{c_i}$ is the correlation coefficient of the i^{th} feature with the output, evaluated across m features.

- *Adaptive Learning Rate:*

$$\alpha_t = \frac{\alpha_0}{1 + \beta_t} \; for\ t = 1, 2, \ldots, T \qquad (21)$$

where, α_t is the learning rate at iteration t, α_0 is the initial learning rate, and β is a decay factor.

- *Stopping Criterion Based on Error Reduction:*

$$if\ E_t - E_{t-1} < \epsilon \qquad (22)$$

The algorithm tracks error development through Et and Et−1 at each iteration to validate that the result achieves a minimum threshold value of ϵ.

An optimization process of IANN architecture occurs through heuristic adjustments of its layers and activation functions to better extract complex data patterns. During training weight, initialization happens through heuristic approaches to speed up the convergence speed. An adaptive learning rate together with heuristic-based modifications forms part of the training process, which enables model prediction refinement through successive iterations. The rainfall prediction system is evaluated thoroughly through traditional method comparison before implementing feedback-based flexibility, which leads to optimized prediction accuracy.

- ***The calculation process for Layer composition, activation functions, weight initialization, adaptive learning rates and performance evaluation appears as follows:***
- *Layer Composition Optimization:*

$$L = L_1, L_2, \ldots, L_k \qquad (23)$$

- ***This definition establishes boundaries for L, which represents the ANN layers, and k represents the total number of these ANN layers. Network layer Li contains a different number of neurons ni.***
- *Activation Function Adjustment:*

$$a_i = f(z_j) \quad where\ z_j = \sum_{i=1}^{n} w_{i,j} x_i + b_j \qquad (24)$$

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where, a_j is the activation of neuron j, f is the activation function (e.g., ReLU, sigmoid), w_{ij} are the weights, x_i are the inputs, and b_j is the bias term.

- *Weight Initialization Heuristic:*

$$w_{ij} = \mathcal{N}(0, \sigma^2)\ for\ i = 1,2,\ldots,n\ and\ j = 1,2,..,m \tag{25}$$

where, w_{ij} is the weight connecting input i to neuron j, and σ^2 is the variance.

- *Adaptive Learning Rate:*

$$\alpha_t = \alpha_0 \cdot \frac{1}{1+\beta t}\ for\ t = 1,2,\ldots.,T \tag{26}$$

where, α_t is the learning rate at iteration t, α_0 is the initial learning rate, and β is a decay factor.

- *Weight Update Rule:*

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} - \alpha t \frac{\partial E}{\partial w_{ij}} \tag{27}$$

where, w_{ij} is the weight at iteration t, and E is the error function being minimized.

- *Performance Evaluation Metric:*

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(yk - \hat{y}k)^2} \tag{28}$$

The calculation uses RMSE Root Mean Square Error alongside yk actual output values combined with predicted values of y^k under the total number of predictions N.

- *Feedback Mechanism for Adaptation:*

$$\Delta w_{ij} = \eta \cdot sign\ (E_t) \tag{29}$$

where, η is the adaptation factor. The weights undergo an adjustment during which they receive feedback from the error Et through this calculation.

The equations establish guidelines for optimization and training of the IANN structure to enhance pattern recognition capabilities during rainfall prediction processes.

8. Experimental Results

The research employs Mean Absolute Error (MAE), Root Mean Square Error (RMSE) together with Custom Accuracy (CA) to measure network loss and predictive performance of the proposed model against conventional models. RF[26] alongside EDT[27] and XGBoost [28] form the set of traditional models that were evaluated.

8.1 Evaluation Metrics

The Custom Accuracy (CA) metric assesses the model's complete accuracy by assessing its predictive ability for rain as well as its ability to detect non-rain conditions. The metric requires customization based on rainfall thresholds when determining specific prediction ranges for rainfall intensity. It can be computed as follows:

$$CA = \frac{TP - TN}{TP + TN + FP + FN} \tag{30}$$

The instances showing correct rainfall predictions are denoted as TP. The model correctly predicts no rainfall in cases classified under TN. The incorrect rainfall prediction by the model when actual rainfall amounts to zero is denoted by FP. FN relates to the cases where the model fails to predict rainfall when it occurs.

8.2 Model Evaluation & Discussion

8.2.1 Statistical Analysis

Figure 2 highlights the correlation heatmap of the features used in the designed big data set, as there are **strong positive correlation** between MinTemp and MaxTemp(0.73), Temp3pm and MaxTemp(0.97) pressure9am and pressure3pm(0.96), cloud9am and cloud3pm(0.56), Humidity9am and Humidity3pm(0.66), Temp9am

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and Temp3pm(0.85), MinTemp and MinTemp3pm(0.70). **Strong negative correlation:** Sunshine and cloud3pm (-0.55), Sunshine and Cloud9am (-0.53)

Figure 3(a) shows the distribution of a key variable, that is, rainfall, while Figure 3(b) is responsible for counting the categorical variable (i.e.,RainTomorrow).

Figure 4(a) is responsible for checking the presence of outliers in the rainfall, while Figure 4(b) shows the outlier free scaled target features.

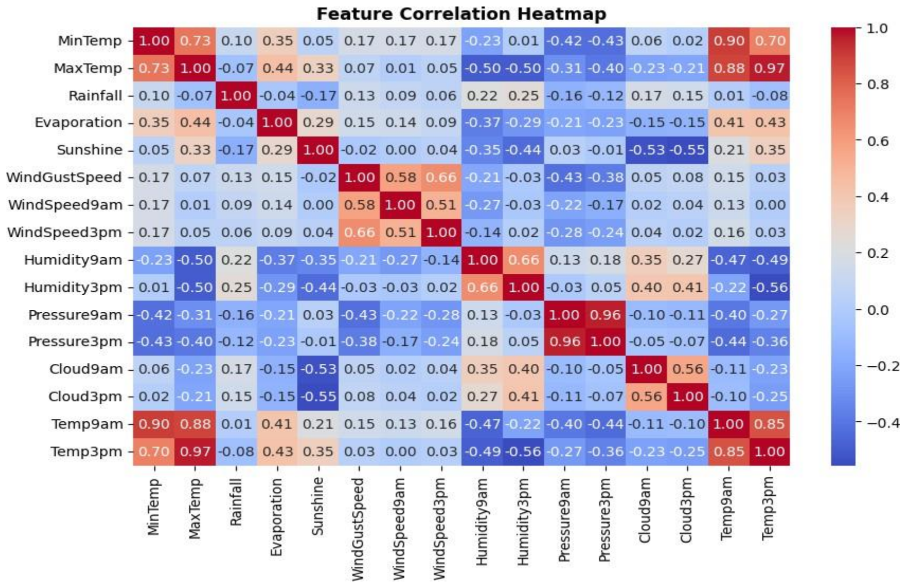
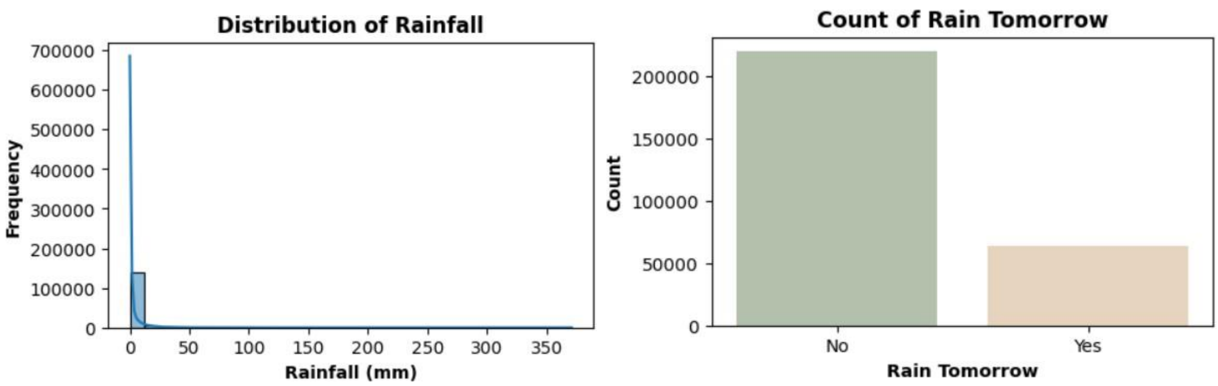


Figure 2. Feature Correlation Heatmap between the Features used in the Designed Big Dataset.

8.2.2 Analysis of the Evaluation Results

Figure 5(a) describes the accuracy of the predicted rainfall of the proposed HI^2NN framework through the designed CA metric, while Figure 5(b) depicts the loss of the proposed HI^2NN framework.

Figure 6 shows the distribution of predicted rainfalls through the proposed HI^2NN framework.



(a) **(b)**

Figure 3. (a) Distribution of the Key Variable of the Designed Big Dataset. (b) Counting the Categorical Variable (i.e., RainTomorrow).

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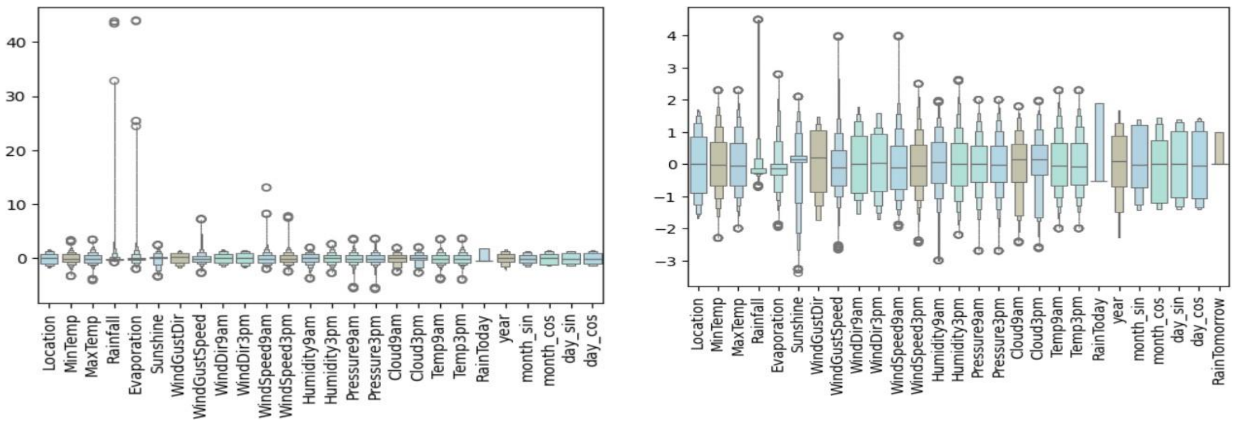
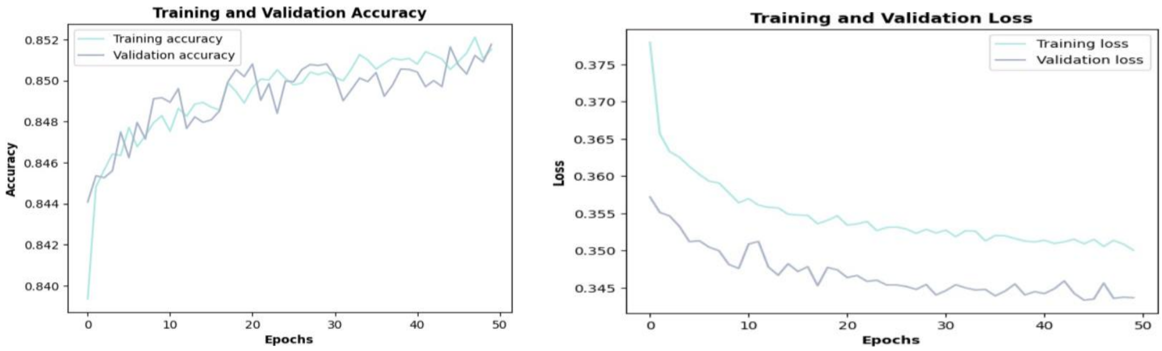


(a) **(b)**

Figure 4. (a) Presence of Outliers in Rainfall. (b) Outlier free Scaled Target Features.



(a) **(b)**

Figure 5. (a) Accuracy of the Predicted Rainfall of the Proposed HI^2NN Framework. (b) Loss of the Proposed HI^2NN Framework.

Figure 7 shows the confusion matrix (CM) of all of the state-of-the-art models.

Table 4 presents a comprehensive comparison of the proposed HI^2NN framework with traditional models, including Random Forest (RF) [26], Ensembled Decision Tree (EDT) [27], and XGBoost [28].

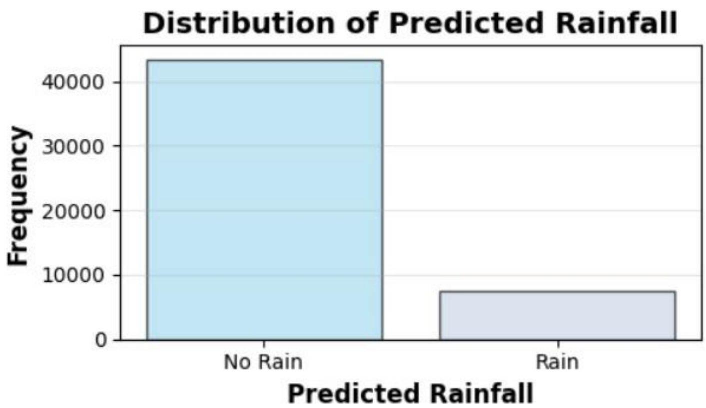


Figure 6. Distribution of Predicted Rainfall through the Proposed HI^2NN Framework.

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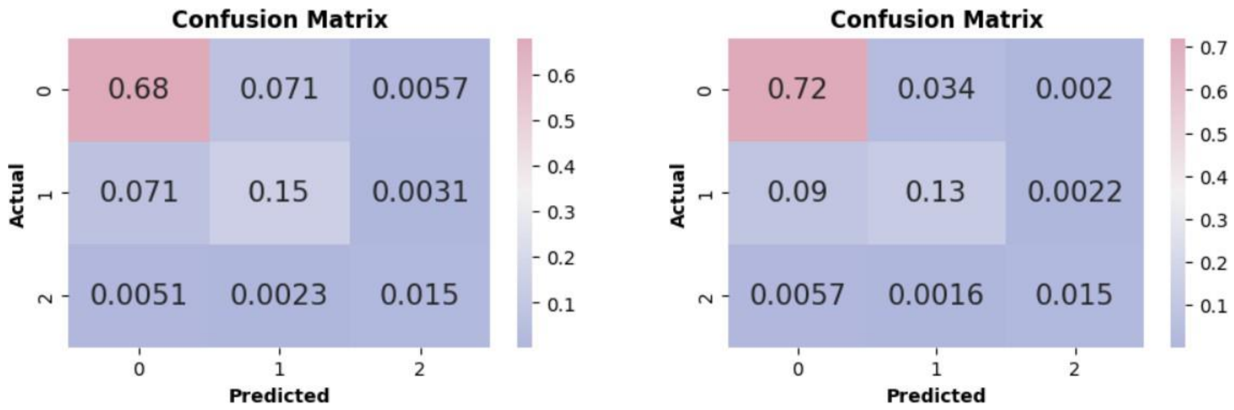

Figure 7. Confusion Matrix of the (a) Proposed *HI²NN* Framework. (b) RF Model. (c) EDT Model. (d) XGBoost Model.

From Table 4, we observed that the performance of various rainfall pre- diction models, including RF [26], EDT [27], XGBoost [28], and the proposed *HI²NN* models, based on three key metrics: MAE, RMSE, and CA. The pro- posed model exhibits the best performance, with the lowest MAE of 0.27 and RMSE of 0.022, indicating predictions that are more accurate compared to RF.

Table 4: Comparison Table.

Framework Model	**/MAE**	**RMSE**	**CA**
RF [26]	0.42	0.32	80%
EDT [27]	0.39	0.35	82%
XGBoost [28]	0.30	0.29	85%
***HI²NN* (Proposed)**	**0.27**	**0.022**	**92%**

(MAE: 0.42, RMSE: 0.32), EDT (MAE: 0.39, RMSE: 0.35), and XGBoost

(MAE: 0.30, RMSE: 0.29). Additionally, it achieves the highest accuracy at 92%, outperforming RF (80%), EDT (82%), and XGBoost (85%). Thus, these results demonstrate the proposed *HI²NN* framework's superior effectiveness in enhancing rainfall prediction accuracy over traditional models.

9. Conclusion & Future Work

- Conclusion

In this study, we presented a novel approach using Heuristic Intelligence integrated with Artificial Neural Networks to enhance rainfall prediction accuracy. Our proposed *HI²NN* model effectively leverages historical weather data, optimizing the prediction process through a combination of neural net- work techniques and heuristic strategies. The results demonstrated significant improvements in prediction performance compared to traditional methods, as evidenced by lower error rates and higher accuracy metrics.

The integration of heuristics into the model allowed for adaptive tuning of parameters, which contributed to the robustness of the predictions under varying climatic conditions. The powerful tool potential of HI²NN reveals its ability to create more dependable meteorological forecasting systems.

- Future Work

Further research should focus on exploring several potential directions because the current model has already demonstrated its capability to deliver positive results.

1. The model requires real-world implementation for rainfall prediction through practical testing to obtain performance data from specific scenarios, which will help verify its effectiveness.

2. The research can benefit from studying different geographical regions to evaluate how well the HI²NN model performs in climates beyond the examined zones.

The researchers focus on implementing future research directions that will enhance the HI²NN framework and weather prediction methodology in order to bolster disaster preparedness and resource management operations.

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