Towards Accurate Rainfall Volume Prediction

Akinsehinde, Bamikole Olaleye; Shang, Changjing; Shen, Qiang

Published in:
Advances in Computational Intelligence Systems

DOI:
10.1007/978-3-031-47508-5_10

Publication date:
2024

Citation for published version (APA):
Akinsehinde, B. O., Shang, C., & Shen, Q. (2024). Towards Accurate Rainfall Volume Prediction: An Initial Approach with Deep Learning, Advanced Feature Selection, Parameter Optimisation, and Ensemble Techniques for Time-Series Forecasting. In *Advances in Computational Intelligence Systems: Contributions presented at the 22n UK Workshop on Computational Intelligence (UKCI 2023), September 6-8 2023, Birmingham, UK* (Vol. 1453, pp. 114-132). (Advances in Computational Intelligence Systems; Vol. 1453). Springer Nature. https://doi.org/10.1007/978-3-031-47508-5_10

Towards Accurate Rainfall Volume Prediction: An Initial Approach with Deep Learning, Advanced Feature Selection, Parameter Optimisation, and Ensemble Techniques for Time-Series Forecasting

Bamikole Olaleye Akinsehinde, Changjing Shang and Qiang Shen

Department of Computer Science, Faculty of Business and Physical Sciences, Aberystwyth University, Aberystwyth, Ceredigion, Wales, UK
{baa32, cns, qqs}@aber.ac.uk

Abstract. Accurate rainfall forecasting is crucial in sectors such as agriculture, transportation, and disaster prevention. This study introduces an initial approach that combines deep forecasting techniques, advanced feature selection, parameter optimisation, and ensemble method to enhance the accuracy of rainfall volume prediction. The proposed methodology is evaluated using a historical weather dataset from Bath, United Kingdom, spanning from January 1, 2000, to April 21, 2020. To address challenges related to generalisation, uncertainty, reliability, and inappropriate predictors, a hybrid mechanism is created by combining various LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) models with a Fuzzy Inference System. The resulting ensemble system comprises five individual hybrid models. Through baseline experiments and comparisons with benchmarks, the effectiveness of the methodology is demonstrated, revealing significant performance improvements over previous studies, across a range of performance indices. Overall, the proposed ensemble approach exhibits better generalisation compared to benchmarks. This research has the potential to revolutionise rainfall volume predictions by leveraging deep learning, advanced feature selection, parameter optimisation and ensemble techniques, overcoming many limitations of the existing approaches.

Keywords: Rainfall Prediction, Weather Forecasting, Deep Learning, Ensemble Techniques. Fuzzy Rough Feature Selection, Optimisation Techniques, Hybrid Method.

1 Introduction

Rainfall forecasting is essential for agriculture, disaster preparedness, and water resource management. However, existing models encounter challenges due to the complexity, uncertainty, and dynamism of weather systems [1, 5, 29, 33]. Issues such as underfitting, overfitting, inappropriate predictor features, and lack of reliability in accounting for uncertainty hinder these models [3, 7, 27]. Overcoming these challenges is crucial for developing improved models that enhance the understanding and prediction of rainfall events, impacting natural and human processes. To address these challenges, a desirable approach would be a hybrid system, as reported in [35, 36], that combines various algorithms and techniques to enhance accuracy and reliability.

Popular deep learning algorithms, such as Long Short-Term Memory (LSTM) [3, 9, 12, 20, 27, 30], and Gated Recurrent Unit (GRU) [2], show promise in capturing temporal dependencies in rainfall data [4, 27]. They are commonly used for sequence modelling and prediction tasks, including time series analysis. By utilising appropriate feature selection methods [6, 13, 14, 16, 17], parameter optimisation, and Fuzzy Inference Systems (FIS) [31, 32], the accuracy of rainfall forecasting can be improved. Ensemble methods can indeed help reduce combined model errors [8, 10, 23, 24].

This study aims to enhance rainfall forecasting accuracy and reliability through the integration of LSTM, GRU, and FIS, in conjunction with advanced feature selection (AFS), parameter optimisation (PO), and ensemble technique (ET). In particular, by exploiting Fuzzy Rough Feature Selection (FRFS) and RandomisedSearchCV for hyperparameter optimisation, the resulting hybrid system can be expected to significantly improve prediction performance.

As an initial attempt to implement the above aim, the following research questions are addressed, with the corresponding solution mechanisms proposed:

1. How does the hybrid approach of LSTM/GRU combined with FIS enhance rainfall forecasting accuracy, as compared to the standalone Bidirectional-LSTM model [3]?
2. Can an AFS technique using Fuzzy Rough Feature Selection based on Fuzzy C-Means Clustering and Rough Membership (FRFS-FCMRM) effectively address underfitting, overfitting, and inappropriate predictive features by selecting only a small number (say, three) of features (excluding the target variable) from a much larger set (of 46 features), compared to the manual approach of selecting (11) features guided by the computation of the Correlation Matrix through Pearson correlation coefficient of a high dimensional datasets [3]?
3. How can rainfall prediction uncertainty be quantified, considering variations in intensity and frequency throughout the year [1, 11, 33]?
4. What are the main advantages and limitations of combining LSTMs [3], GRUs [2], and FIS [21] in a hybrid system [2] for rainfall forecasting, and how does RandomisedSearchCV [2, 3] and FIS optimise performance?

With reference to the earlier study [3], this study utilises the historical weather data (HWD) from Bath City, United Kingdom (UK), obtained through a subscription to the History Bulk download provided by OpenWeather Limited, United Kingdom[1]. The HWD from 1st January 2000 to 21st April 2020, is used to train the nine setup models for this study. The performance of the resulting hybrid and proposed models is compared against that of baseline and benchmark [3] models. This study contributes to advancements in rainfall forecasting accuracy, addressing challenges faced by existing models [1, 3, 4, 25, 27, 30].

[1]Data Source, http://openweathermap.org

The proposed ensemble system (Hybrid LSTM-GRU-FIS-RandomisedSearchCV) offers a novel approach that overcomes the major limitations of benchmark [3] models. It improves generalisation, reduces uncertainties, ensures reliable feature selection, optimises model parameters, and achieves superior performance in rainfall volume predictions. The summary of the main contributions of this study are:

- Generalisation improvement: By combining LSTM, GRU, and FIS techniques, the ensemble system enhances generalisation for accurate predictions across diverse scenarios and datasets.
- Uncertainty reduction: The ensemble model reduces uncertainties and helps mitigate biases by integrating predictions from multiple hybrid models, thereby combining the strengths of individual models and providing a comprehensive understanding of rainfall patterns. It achieves accounting for fluctuations in intensity and frequency across different season, leveraging the power of deep learning and FIS.
- Reliable feature selection: The core mechanism, FRFS-FCMRM, utilises Fuzzy C-Means Clustering and Rough Membership values to select the most relevant features, addressing the issue of inappropriate predictors in the benchmark models.
- Parameter optimisation: RandomisedSearchCV optimises parameters for each hybrid model, ensuring optimal performance in predicting rainfall volume.
- Performance improvements: The ensemble system exhibits significant enhancements over benchmarks, achieving superior accuracy and reliability in predicting rainfall volume.

The rest of this paper is organised as follows. Section 2 reviews the closely relevant work to the present research. Section 3 details the proposed methodological approach. Section 4 discusses the setup predictive models, Section 5 reports on the initial results of the experimental investigation regarding the performance of the proposed approach. Section 6 concludes this work and points out directions for further developments.

2 Related Work

This section provides an overview of the existing literature focused on enhancing the accuracy and reliability of rainfall forecasting. The reviewed literature highlights the advancements made in rainfall forecasting methodologies (RFM), emphasising the importance of incorporating different data sources, AFS, deep learning models, ensemble methods, and hybrid machine learning (ML) techniques. By examining the relevant work, this review delves into the key aspects associated with accurate predictions, offering valuable insights into recent advancements in improving RFM [1, 3, 4, 25, 27].

A comprehensive analysis of relevant techniques in this area has emphasised the importance of incorporating different data sources [2] and predictors [3] to improve accuracy in rainfall forecasting while reducing uncertainties [5] in weather station data.

AFS techniques, such as FRFS [6, 28], can reduce model complexity and improve performance.

Artificial neural networks (ANN) like LSTM and GRU have been examined for capturing temporal dependencies in rainfall data [3, 20, 34]. In a recent benchmark study [3], various models were evaluated for hourly rainfall forecasting using HWD datasets from five UK cities. The LSTM-based models, including Stacked-LSTM and Bidirectional-LSTM, outperformed other models, including Extreme Gradient Boosting (XGBoost) and classical ML approaches (CMLA). These results indicate that LSTM-based models can achieve better performance in rainfall volume prediction. Hence, LSTM architectures are adapted as the hybrid model components in this original study.

The deployment of the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)-Convolutional Neural Network (CNN)-GRU model, which involves deep learning techniques, for time series forecasting of soil moisture [2], has provided valuable insights for rainfall volume prediction. By integrating diverse data sources such as satellite-derived data, climate indices, and ground-based variables, the hybrid CEEMDAN-CNN-GRU system outperforms other models in terms of statistical metrics and infographics, demonstrating the potential of hybrid models for accurate rainfall volume prediction. The use of ensemble methods and hyperparameter tuning further improves the system's performance.

The simple averaging ensemble approach [26] has proven successful in various domains, such as wastewater treatment plant prediction using artificial intelligence models. Similarly, the ensemble method that implements assigning weights to ensemble members helps effectively reduce uncertainties in rainfall-runoff simulations and flood risk predictions [8]. Drawing inspiration from the use of ensemble methods in operational space weather forecasting [24], where they have enhanced models and forecasts. Combining the efficiency of ensemble methods with hybrid models is promising in improving the accuracy and reliability of rainfall prediction.

Integration of design choices in ML algorithms enhances model performance for time series problems, as seen in studies involving Neuro-Fuzzy Inference Systems [31] and hybrid fuzzy intelligent agent-based systems [36]. Additionally, hybrid ML techniques, such as the Neural Fuzzy Inference System-Based Weather Prediction Model (NFIS-WPM) [21], have shown improved outcomes in weather forecasting. These models combine fuzzy rule-based neural networks with neural fuzzy inference systems, achieving improved accuracy in precipitation predictions compared to conventional ANN. Furthermore, the Generalised Dynamic Fuzzy Neural Network (GDFNN) model has been introduced for short-term wind speed forecasting, overcoming overfitting issues through optimisation with the brainstorm optimisation algorithm [22]. These insights serve as a foundation for the proposed approach in this study.

Considering the various design choices and approaches as reviewed in this section, the LSTM architecture, including unidirectional LSTM (LSTM), Bidirectional LSTM (BiLSTM), stacked LSTM (StLSTM), and multi-layer LSTM (MtLSTM), along with Gated Recurrent Unit (GRU) and FIS, are being adapted in this original study. Additionally, techniques such as RandomisedSearchCV and ensemble methods are incorporated to perform accurate and reliable rainfall forecasting, as detailed below.

3 Methodology

This section describes an initial approach working towards accurate and reliable rainfall volume forecasting through two major computational processes: the baseline and the hybrid. The methodology can be summarised as the architecture depicted in Fig. 1.

The following subsections discuss the component steps involved, including data collection, data preprocessing, setup of baseline models, and the later section discusses the configuration of various hybrid models. Additionally, the hybrid models are integrated using ensemble techniques.

3.1 Architecture

Figure 1 provides an overview of the architectural design for the approach undertaken in this research. It incorporates techniques such as deep forecasting, feature selection, parameter optimisation, and model ensemble to improve rainfall predictions performance.

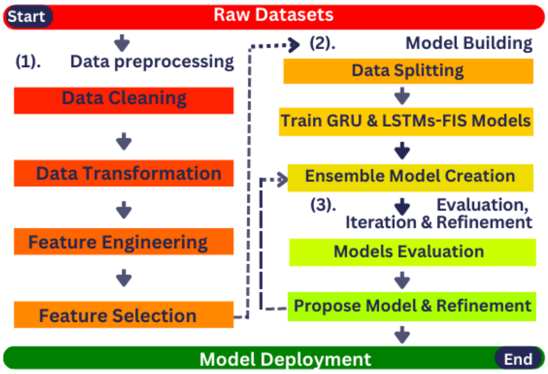

Fig. 1. Flowchart of the proposed framework.

3.2 Data Collection and Pre-processing

The raw historical weather dataset (HWD) from Bath city in the UK is utilised in this study. It contains various weather-related measurements recorded at regular intervals, including temperature, humidity, pressure, wind speed, precipitation, and other meteorological features. Table 1 shows all the features in the dataset, along with the description of the weather element.

Table 1. All features in Bath dataset, with description and percentage of missing values.

S/N	Variable Name	Description of Variable	Missing Value		S/N	Variable Name	Description of Variable	Missing Value
01	dt	Time of data calculation	0.00%		15	grnd_level	Earth surface	100%
02	dt_iso	Date and time in UTC.	0.0%		16	humidity	Percentage of humidity	0.0%
03	timezone	UTC shift (sec)	0.0%		17	wind_speed	Wind Speed	0.0%
04	city_name	City name	0.0%		18	wind_deg	Wind direction	0.0%
05	lat	Latitude	0.0%		19	wind_gust	Brief increase in wind speed	94.0%
06	lon	Longitude	0.0%		20	rain_1h	Hourly rainfall volume	83.4%
07	temp	Temperature	0.0%		21	rain_3h	3-hour rainfall volume	100%
08	visibility	Average visibility (metres)	87.5%		22	snow_1h	Hourly Snow volume	99.7%
09	dew_point	Droplet formation temperature.	0.0%		23	snow_3h	3-hour rainfall volume	100%
10	feels_like	Weather perception	0.0%		24	clouds_all	Percentage of cloud cover	0.0%
11	temp_min	Minimum temperature	0.0%		25	weather_id	Weather condition id	0.0%
12	temp_max	Maximum temperature	0.0%		26	weather_main	Weather parameter group	0.0%
13	pressure	Atmospheric pressure.	0.0%		27	weather_description	Group weather state	0.0%
14	sea_level	Level of sea surface	100%		28	weather_id	Weather condition id	0.0%

The following sub-sections describe several data preprocessing steps undertaken to clean and prepare the dataset for subsequent analysis and verification of the proposed approach.

3.2.1 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is conducted to gain insights into the dataset, using summary statistics and visualisations such as box plots, histograms, scatter plots, and correlation analysis to understand the data structure and identify any issues. The line graph depicted in Fig. 3, 4, 5 and 6 offer insights into patterns of the target (forecast) variable and the three associated most important features. The visualisation reveals variations in a number of aspects, including: (1) rainfall intensity and frequency, (2) atmospheric pressure, (3) temperature, and (4) degree of wind throughout the year. These observations indicate a complex system which demands accurate and reliable rainfall prediction models that can capture the sophisticated patterns of such nature.

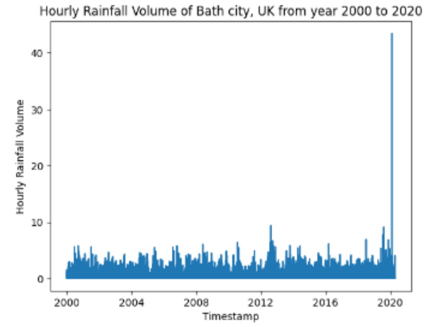

Fig. 2. Hourly Rainfall Volume.

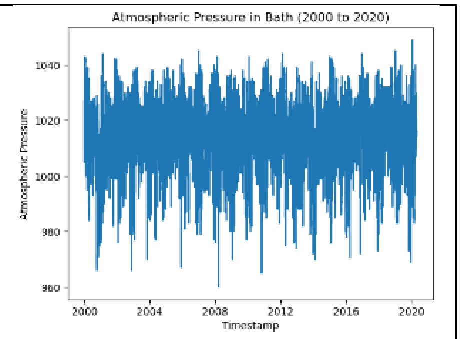

Fig. 3. Atmospheric Pressure.

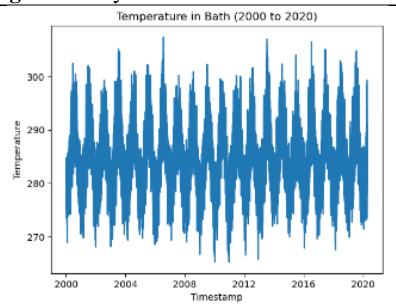

Fig. 4. Temperature in Bath.

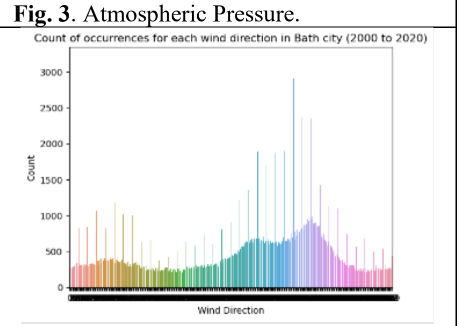

Fig. 5. Degree of Wind direction.

3.2.2 Data Cleaning and Missing Value Treatment

The HWD dataset initially contains missing values and null entries. Fig. 6 presents the bar chart with the missing numbers depicted.

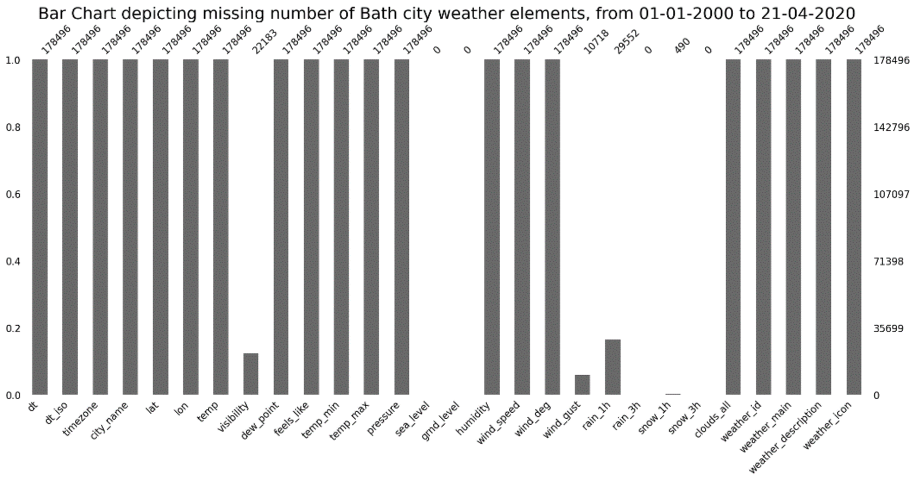

Fig. 6. Missing Data: Bar Chart of Bath - Missing and Nullness of Features (2000-2020).

Data cleaning is an essential step that involves addressing missing values and eliminating irrelevant features in this initial approach. The following steps are taken for data cleaning and missing value treatment:

(1) **Null variables**: Null features (whose values are largely missing) are identified and dropped from the dataset. Of such is the "visibility" variable being removed due to its having 87.57% missing values, as statistical analysis of such variables reveals little or no impact on the target variable (rain_1h). Similarly, "wind_gust" has 94% missing values and hence, is removed, and "sea_level," "grnd_level," "rain_3h," and "snow_3h" measurements are also discarded due to their 100% missing values.
(2) **Irrelevant Features**: Obviously unnecessary features for the present objectives are excluded. These include the feature "city_name", as the dataset is already separated by city during collection (and herein, only the subset of data taken for Bath city is utilised). The "dt" feature (time of data calculation) is removed since the "dt_iso" feature already contains date and time information. The "+0000 UTC" string is removed from the dt_iso column, with the column converted into datetime format. The dataFrames are filtered to include HWD from 2000-01-01 00:00:00 to 2020-04-21 00:00:00, to facilitate a comparative analysis with an earlier study [3]. The "timezone" feature is also excluded to avoid restricting the learning process of the models to highly specific time patterns.
(3) **Missing Values:** To handle missing values in specific features such as "rain_1h," "snow_1h," and "snow_3h," where the amount of the missing ones is limited, the

missing values are imputed with zeros. Imputing these features with zeros assumes that if a value is absent for any hour, it indicates no precipitation during that period.

3.2.3 Feature Extraction

Feature extraction is applied here to the pre-processed dataset, expanding the variable description (from the original 27 to 46). The focus is on the categorical feature "weather_main," summing information on different weather parameters. It is grouped using "weather_id" and encoded as 0 or 1 to indicate the absence or presence of a specific weather condition, respectively. The original features "weather_main," "weather_description," and "weather_id" therefore become redundant and are dropped, with (19) new and raw features created through one-hot encoding [3]. This feature extraction process provides valuable insights into variable relationships. After running feature extraction, the Bath city HWD dataset consists of 46 features.

3.2.4 Feature Selection – Removing Multicollinearity Features

Feature selection helps address the problem of feature multicollinearity while maintaining the semantics of those selected ones. To improve forecasting models, addressing multicollinearity is crucial. Selecting a reduced set of relevant features for the target variable enhances the reliability, accuracy, and robustness of rainfall forecasting models. As a popular feature selection tool, FRFS provides a means to identify relevant features for rainfall prediction, ensuring the final feature set to be most relevant to the target variable (rain_1h) for an explainable, generalised, and accurate prediction system.

Feature Selection for Baseline model 1 through FRFS-CMM: The first baseline model (BM1) applies a conjunctive approach of FRFS and the Correlation Matrix Method (CMM) [3]. Fig. 7 displays the correlation value of variables in the Bath city dataset. The heatmap assists in conducting correlation analysis, helping to identify variable relationships to address multicollinearity issues.

To implement FRFS and automate the selection of important predictive features, the initial step involves identifying variables with correlations equal to or greater than the set threshold (i.e., 0.7 for the present work), following established practices in the literature. By defining the correlation threshold as 0.7, those (39) predictive features (below the threshold) are obtained from the initial (46) ones. Variables such as "dew_point," "feels_like," "temp_min," "temp_max," "snow_1h," and "Snow_id_601" are identified as highly correlated features based on the threshold and subsequently dropped. The selected independent variable for BM1 is split into a training, validation, and test set as inputs for BM1 with the target variable "rain_1h”. Table 2 shows the resulting list of independent selected variables for BM1 and other models.

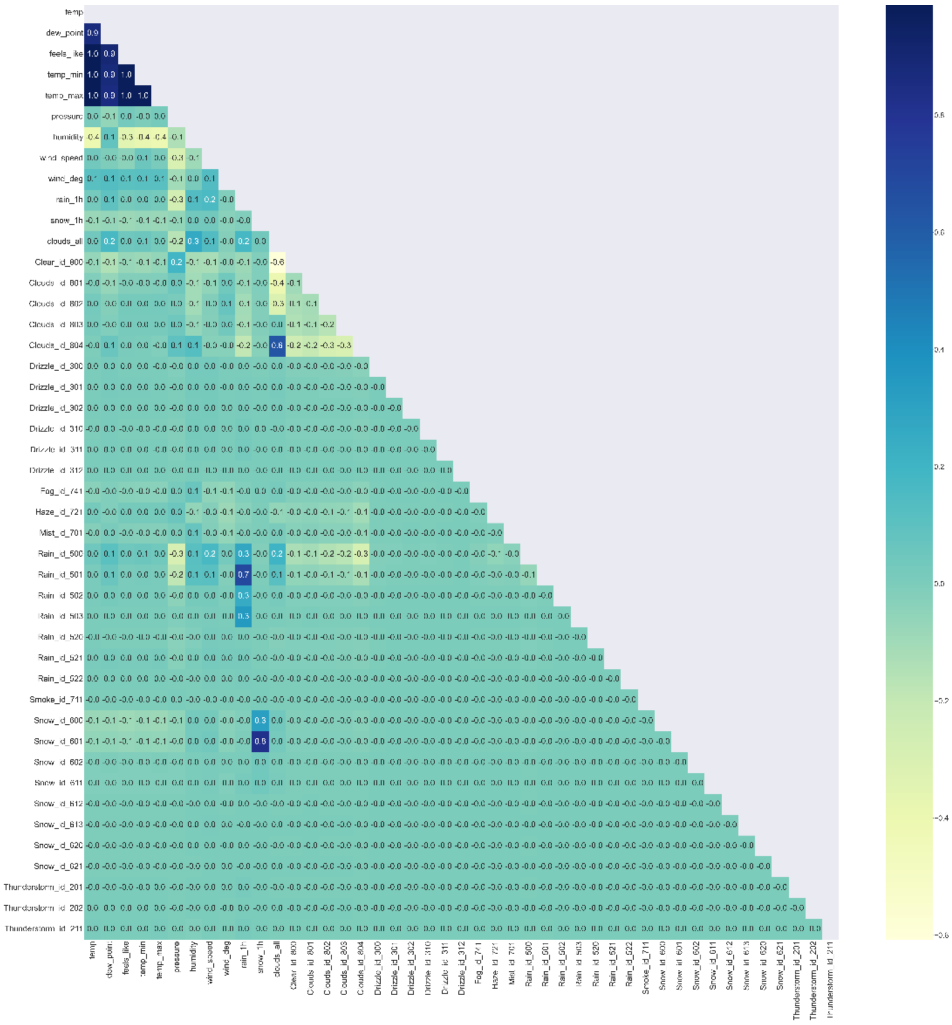

Fig. 7. Heatmap for variables in Bath city dataset (01/01/00-21/04/20).

Feature Selection for Baseline models 2 and 3 through FRFS-FCMRM: The core feature selection mechanism for the proposed rainfall forecasting system is FRFS-FCMRM, which utilises Fuzzy C-Means Clustering and Rough Membership values to determine feature importance. The top five features are selected through this approach and undergo preprocessing (splitting, standardisation) for training and evaluation. The second baseline model (BM2) validates FRFS in a multi-dimensional dataset using these five important features. BM2 broaden the understanding of the importance of using the optimal minimum of the most important variables, as opposed to utilising a larger set of features (39 features) as done by BM1. Because BM2 exhibits similar metric performance with BM1, while offering the benefits of model simplicity, interpretability, reduced overfitting and computational efficiency, it paves the way for discovery the optimal number of features for Baseline model 3 (BM3). BM3 employs the three most important features achieved through FRFS-FCMRM as independent input variables while utilising the LSTM algorithm. Determining the optimal number of input features through BM models is a crucial starting point for building the hybrid models. Table 2 provides the list of features that are used to train all the models (BM1, BM2, BM3, the hybrid and ensemble models).

Table 2. List of feature sets used to train all models.

Type of Model	Baseline Model 1 (BM1)	Baseline Model 2 (BM2)	Baseline Model 3 (BM3)	The five Hybrid Models	Ensemble (Proposed) Model
Implemented Technique	Conjunctive application of FRFS and CMM (FRFS-CMM)	FRFS-FCMRM	FRFS-FCMRM	FRFS-FCMRM	FRFS-FCMRM
Selected Variables	temp, pressure, humidity, wind_speed, wind deg, snow 1h, clouds_all, Clear_id_800, Clouds_id_801, Clouds_id_802, Clouds_id_803, Clouds_id_804, Drizzle_id_300, Drizzle_id_301, Drizzle_id_302, Drizzle_id_310, Drizzle_id_311, Drizzle_id_312, Fog_id_741, Haze_id_721, Mist_id_701, Rain_id_500, Rain_id_501, Rain_id_502, Rain_id_503, Rain_id_520, Rain_id_521, Rain_id_522, Smoke_id_711, Snow_id_600, Snow_id_602, Snow_id_611, Snow_id_612, Snow_id_613, Snow_id_620, Snow_id_621, Thunderstorm_id_201, Thunderstorm_id_202, Thunderstorm_id_211.	pressure, temp, wind_deg, humidity, and clouds_all	pressure, temp, wind_deg	pressure, temp, wind_deg	pressure, temp, wind_deg

4 Modelling

This section focuses on the development of baseline models (BM1, BM2, BM3) and that of the five predictive hybrid models (LSTM-FIS, bidirectional LSTM-FIS, Stacked LSTM-FIS, multi-layer LSTM-FIS, GRU-FIS), involving parameter optimisation and model validation. It also specifies how individual hybrid models are integrated through ensembles to create different implementations of the proposed approach, aiming to achieve accurate and reliable rainfall prediction.

4.1 Baseline Models

The baseline models (BMs) are set up to determine the optimal number of selected features that will yield the best performance in predicting rainfall volume. This approach of employing standalone LSTM variants (unidirectional LSTM) follows the conventional method used in earlier studies [3]. The decision to use a minimal set of three selected features as input in the subsequent construction of the hybrid model with the target variable is guided by these baseline models, aiming to achieve an enhanced and accurate rainfall prediction model through model integration. Additionally, the baseline models serve as a systematic means of comparing the performances of different algorithm combinations in the hybrid model.

Three LSTM models, namely BM1, BM2, and BM3, are built as baseline models. They only differ in terms of input features. For the present implementation, BM1 utilises 39 features as independent variables selected through FRFS-CMM. BM2 uses five selected independent variables, along with the target variable (rain_1h). BM3 utilises the top three most important features, selected through the same FRFS-FCMRM method. The features employed by each model are listed on Table 2.

The baseline models (BM1, BM2 and BM3) employ a unidirectional LSTM with a batch size of 64, 150 epochs, and a patience of 100. The primary purpose of the baseline models is to determine the dimensionality (or the number of independent variables) of hybrid models, aiming to enhance generalisation, prevent overfitting, and reduce complexity in the model architecture.

4.2 Five Predictive Hybrid Models

Through adapting the standalone LSTM-based models [3], including GRU [2] and FIS [21,22,36], five predictive hybrid models for rainfall volume prediction are built through the combination of FIS with LSTM variants, namely, unidirectional LSTM, bidirectional LSTM, stacked LSTM, multi-layer LSTM (respectively referred to as LSTM, BiLSTM, StLSTM, MtLSTM, hereafter) and GRU. This leads to the hybrid models of LSTM-FIS, BiLSTM-FIS, StLSTM-FIS, MtLSTM-FIS, and GRU-FIS.

Note that GRU is a modified version of LSTM and is also a type of recurrent neural network (RNN). As with LSTM, GRU is designed to handle sequential data and address the vanishing gradient problem that can occur in traditional RNNs. The five-hybrid models are all designed with an input shape of (1, 3). This implies that each sample in the data is represented by a single time step with three features, as used with BM3.

These models utilise a layer consisting of 30 units to control complexity in a similar way to the BMs. Mean squared error (MSE) is used as the loss function, and the 'adam' optimiser [3] is exploited.

The training process involves iterations over the dataset for a specified number of epochs, which can be chosen from a grid of values like 10, 20, and 50. Batch size (32, 64, and 72), i.e., the number of samples processed before updating the model, is also adjustable. RandomisedSearchCV is used for training with the meta-parameter monitor='loss' and patience=30. These parameters will of course affect the architecture, optimisation, and training of the hybrid (LSTM-FIS and GRU-FIS) models.

4.3 Integrated Hybrid Model (Ensemble Model)

The success of utilising simple-averaging ensemble approach [26] in various problem domains provides valuable insights for its applications to addressing the challenges of accurate and reliable rainfall volume prediction. In recognition of the above, this study combines the strengths of different hybrid models (based on LSTM and GRU) to help reduce their individual weaknesses, variance, and bias, leading to more reliable rainfall forecasts.

The proposed ensemble system is created using the RandomForestRegressor algorithm and trained on the same weather data acquired from Bath city as used for developing individual predictive hybrid models (namely, LSTM-FIS, BiLSTM-FIS, StLSTM-FIS, MtLSTM-FIS, and GRU-FIS) being integrated as an ensemble model (Hybrid LSTM-GRU-FIS-RandomisedSearchCV) to make predictions on the test data. The individual predictions of the hybrid models are integrated using the simple averaging ensemble approach. This leads to novel contributions to the literature, including the combination of LSTM variants with FIS and that of GRU with FIS, for predicting rainfall volume or other weather conditions, as well as the integration of hybrid models through an ensemble method to enhance rainfall or weather (element) forecasting.

5 Experimental Investigation

To verify the potential of the proposed approach, initial experimental evaluations are carried out in this section.

5.1 Performance Criteria

Following the existing literature [3, 9, 27, 30], the following criteria are utilised to evaluate the performance of all models in this comparative experimental study:

1. Loss: Measuring the discrepancies between predicted and actual outputs, indicating the extent of incorrect predictions.
2. RMSE (Root Mean Squared Error): Quantifying the discrepancies between predicted and actual values, emphasising significant errors.
3. RMSLE (Root Mean Squared Logarithmic Error): Determining the accuracy of predictions on a logarithmic scale, suitable for variables with a wide value range or outliers.

4. MAE (Mean Absolute Error): Measuring the average absolute divergence between predicted and actual values, providing an estimation of typical prediction inaccuracy.

The above performance metrics provide insights into the accuracy and reliability of the predictions made by different models, with lower values indicating better performance.

5.2 Results and Observations

5.2.1 Results and Performance of Compared Models

The performance outcomes (as per Loss, RMSE, RMSLE and MAE) for all compared models are presented in Table 3 and Fig. 8. Each predicted value is also compared with the actual rainfall volume using the proposed model in Table 4. In addition, the performance of different models is compared against the benchmark models [3].

Table 3. Performance of all different models

Type of Experiment	Model Name	Input Feature (No)	Loss Performance	Test Loss	RMSE Performance	Test RMSE	Test RMSLE	Test MAE
Baseline	BM1	39	Rated 2	0.1087	Rated 2	0.3297	0.1944	0.1579
Baseline	BM2	5	Rated 3	0.1096	Rated 3	0.3310	0.1946	0.1582
Baseline	BM3	3	Rated 1	0.1032	Rated 1	0.3212	0.1911	0.1569
Main	LSTM-FIS	3	Rated 4	0.1204	Rated 5	0.3470	0.1981	0.1605
Main	BiLSTM-FIS	3	Rated 3	0.1137	Rated 3	0.3371	0.1981	0.1591
Main	StLSTM-FIS	3	Rated 6	0.1403	Rated 6	0.4125	0.2947	0.3415
Main	MtLSTM-FIS	3	Rated 5	0.1204	Rated 4	0.3431	0.1963	0.1644
Main	GRU-FIS	3	Rated 2	0.1108	Rated 2	0.3329	0.1944	0.1558
Main	Ensemble	3	Rated 1	-0.062	Rated 1	0.3256	0.1974	0.1622

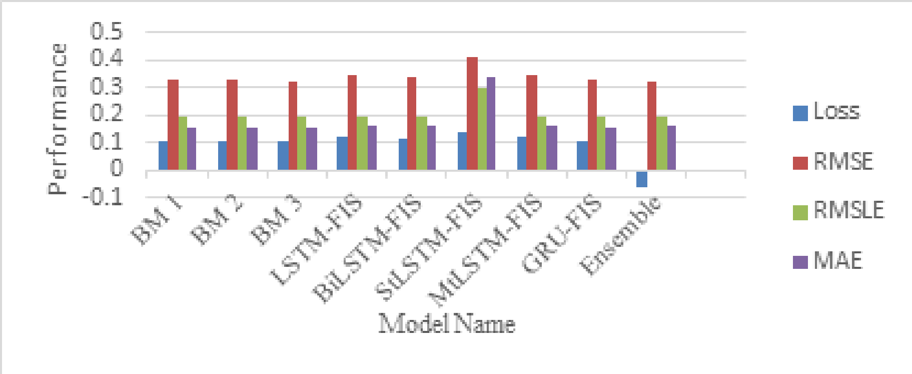

Fig. 8. Model performance

Table 4. Observed and predicted rainfall volumes including percentage accuracy at each timestamp using ensemble (integrated Hybrid LSTM-GRU-FIS-RandomisedSearchCV) model.

S/N	Index_1	Index_2	Observed	Predicted	% Accuracy of Prediction
1	302768	1	0.10	0.097019	97.019464
2	190052	14	0.12	0.096395	80.328969
3	251794	21	0.14	0.097647	69.747988
4	253323	36	1.45	0.097111	6.697309
5	330959	41	0.18	0.097096	53.941992
6	194209	45	0.50	0.097317	19.463494
7	270717	51	0.55	0.097125	17.659052
8	248653	52	1.19	0.097113	8.160774
9	240122	57	0.12	0.097727	81.439006
10	310880	84	0.51	0.098724	19.357673
11	299199	86	0.16	0.096817	60.510384
12	362647	101	0.11	0.096200	87.454387

Table 4 displays observed and predicted rainfall volumes along with prediction accuracy calculated over hourly measurements, using the proposed integrated hybrid LSTM-GRU-FIS-RSCV (ensemble) system. Index_1 indicates the index number in the preprocessed dataset, while Index_2 represents the index number for non-zero rainfall volume (rain_1h). The first twelve timestamps of the predicted values are shown for discussion.

5.2.2 Performance comparison

The ensemble model is shown to achieve the best performance in terms of RMSE and Loss over the tests, surpassing expected accuracy levels. The hybrid models, particularly the GRU-FIS model, exhibit robustness to uncertain data and provide more accurate and reliable predictions. The proposed system, of integrated hybrid LSTM-GRU-FIS-RandomisedSearchCV (ensemble), performs the best with a test Loss of -0.061956, RMSE of 0.325547, RMSLE of 0.1974, and MAE of 0.162241.

Comparing the performance of the resulting system to that attainable in the previous study [3], the proposed approach and hybrid models outperform the benchmark ensemble prediction, achieving lower RMSE values. The benchmark models [3] in the existing work encounter challenges in adapting to abrupt changes and suffer from generalisation limitations, thereby often resulting in inaccurate predictions. In sharp contrast, the proposed approach enables better generalisation with superior accuracy.

The experimental results have highlighted the effectiveness of both the ensemble model and the hybrid LSTM-FIS and GRU-FIS models in predicting rainfall volume, outperforming alternative approaches in terms of accuracy and reliability. The integration of LSTM/GRU with FIS facilitates the capturing of long-term dependencies and temporal patterns. In particular, the use of FIS helps address the challenge of handling uncertain and imprecise data, enhancing model interpretability.

6 Conclusion

This research has presented an initial experiment-based investigation that showcases the potential of integrating deep learning, advanced feature selection, and ensemble techniques to strengthen rainfall volume forecasting. The proposed methodology has been demonstrated to be able to offer superior performance in terms of generalisation, interpretability and accuracy.

This original study has employed a low-quality raw dataset, which may have contributed to differences between predicted and observed values. Missing values in the weather dataset need to be addressed in future work. Further improvement of the integrated system's accuracy and reliability can be expected, by incorporating additional data sources such as satellite and remote sensing data, along with standardised datasets, and exploring a wider range of model hyperparameters. This remains active research. Continual efforts to refine and expand the integrated model through additional data sources and parameter optimisation will contribute to even more precise rainfall volume prediction, benefiting various industries that rely on accurate predictions.

Declaration
This work is free from any financial interest, competing interest, or personal interest that could influence its outcome.

Acknowledgements
The authors would like to acknowledge Barrera-Animas et al., 2021, for their benchmark study. The first author is grateful to Aberystwyth University for offering the PhD scholarship in support of this research.

References

1. Aguasca-Colomo, Castellanos-Nieves, Méndez. Comparative Analysis of Rainfall Prediction Models Using Machine Learning in Islands with Complex Orography: Tenerife Island. Applied Sciences 9:4931 (2019).
2. Ahmed, A.A.M,, Deo, R.C., Raj, N., Ghahramani, A., Feng, Q., Yin, Z., Yang, L. Deep Learning Forecasts of Soil Moisture: Convolutional Neural Network and Gated Recurrent Unit Models Coupled with Satellite-Derived MODIS, Observations and Synoptic-Scale Climate Index Data. Remote Sensing 13:55 (2021).
3. Barrera-Animas, A.Y., Oyedele, L.O., Bilal, M., Akinosho, T.D., Delgado, J.M.D., Akanbi, L.A. Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting. Machine Learning with Applications 100204 (2021).
4. Basha, C.Z., Bhavana, N., Bhavya, P., V. S. Rainfall Prediction using Machine Learning & Deep Learning Techniques. In: IEEE Xplore (2020).
5. Buizza, R. Chaos and Weather Prediction. In: ECMWF (2002).
6. Cornelis, C., Jensen, R., Shen, Q. Hybrid Fuzzy-Rough Rule Induction, and Feature Selection. In: Aberystwyth Research Portal (2009).
7. Deman, V.M.H., Koppa, A., Waegeman, W., MacLeod, D.A., Bliss Singer, M., Miralles, D.G. Seasonal prediction of Horn of Africa long rains using machine learning: The pitfalls of preselecting correlated predictors. Frontiers in Water 4 (2022).
8. Doycheva K., Horn G., Koch C., Schumann A., König M. Assessment, and weighting of meteorological ensemble forecast members based on supervised machine learning with application to runoff simulations and flood warning. AEI33:427–439 (2017).
9. Gauch, M., Kratzert, F., Klotz, D., Nearing, G., Lin, J., Hochreiter, S. Rainfall–runoff prediction at multiple timescales with a single Long Short-Term Memory network. Hydrology and Earth System Sciences 25:2045–2062 (2021).
10. Gneiting, T., Raftery, A. E. ATMOSPHERIC SCIENCE: Weather Forecasting with Ensemble Methods. Science 310:248–249 (2005).
11. GOV.UK; UK Department for Business, Energy and Industrial Strategy- Average annual rainfall in the United Kingdom (UK) from 2001 to 2022. (Statista 2023)
12. Hu, C., Wu, Q., Li, H., Jian, S., Li, N., Lou, Z. Deep Learning with a Long Short-Term Memory Networks Approach for Rainfall-Runoff Simulation. Water 10:1543 (2018).
13. Jensen, R., Mac Parthaláin, N. Towards scalable fuzzy–rough feature selection. Information Sciences 323:1–15 (2015).
14. Jensen, R, Shen, Q. Computational Intelligence and Feature Selection (2008).
15. Jensen, R., Shen, Q. New Approaches to Fuzzy-Rough Feature Selection. IEEE Transactions on Fuzzy Systems 17:824–838 (2009).
16. Ji, W., Pang, Y., Jia, X., Wang, Z., Hou, F., Song, B., Liu, M., Wang, R. Fuzzy Rough Sets and Fuzzy Rough Neural Networks for Feature selection: a Review. WIREs Data Mining and Knowledge Discovery 11(3), e1402 (2021).
17. Li, Ft., Shang, C., Li, Y., Shen, Q. Feature ranking-guided fuzzy rule interpolation. IEEE Press (2017).

18. Li, F., Shang, C., Li, Y., Yang, J., Shen, Q. Fuzzy Rule Based Interpolative Reasoning Supported by Attribute Ranking. IEEE Transactions on Fuzzy Systems 26:2758–2773 (2018).
19. Li, F., Shang, C., Li, Y., Yang, J., Shen, Q. Approximate reasoning with fuzzy rule interpolation: background and recent advances. SpringerLink 54:4543–4590 (2021).
20. Lindemann, B., Müller, T., Vietz, H., Jazdi, N., Weyrich, M. A survey on long short-term memory networks for time series prediction. Procedia CIRP 99:650–655 (2021).
21. Lu, J., Xue, S., Zhang, X., Zhang, S., Lu, W. Neural Fuzzy Inference System- Based Weather Prediction Model and Its Precipitation Predicting Exp. Atm 5:788–805 (2014).
22. Ma, X., Jin, Y., Dong, Q. A generalized dynamic fuzzy neural network based on singular spectrum analysis optimized by brainstorm optimization for short-term wind speed forecasting. Applied Soft Computing 54:296–312 (2017).
23. Maqsood, I., Khan, M., Abraham, A. An ensemble of neural networks for weather forecasting. Neural Computing and Applications 13 (2004).
24. Murray SA. The Importance of Ensemble Techniques for Operational Space Weather Forecasting. Space Weather 16:777–783 (2018).
25. Nayak, D.R., Mahapatra, A., Mishra, P. A Survey on Rainfall Prediction using Artificial Neural Network. Int. Journal of Computer Applications 72:32–40 (2013).
26. Nourani, V., Elkiran, G., Abba, S.I. Wastewater treatment plant performance analysis using artificial intelligence – an ensemble approach. Water Science and Technology 78:2064–2076 (2018).
27. Poornima, S., Pushpalatha, M. Prediction of Rainfall Using Intensified LSTM Based Recurrent Neural Network with Weighted Linear Units. Atmosphere 10:668 (2019).
28. Qian, Y., Wang, Q., Cheng, H., Liang, J., Dang, C. Fuzzy-rough feature selection accelerator. Fuzzy Sets and Systems (2015).
29. SciJinks. How Reliable Are Weather Forecasts? | NOAA SciJinks – All About Weather. In: Scijinks.gov. (2016).
30. Siami-Namini, S., Tavakoli, N., Namin, A.S. The Performance of LSTM and BiLSTM in Forecasting Time Series. 2019 IEEE International Conference on Big Data (2019).
31. Sun, Z-L., Au, K-F., Choi, T-M. A Neuro-Fuzzy Inference System Through Integration of Fuzzy Logic and Extreme Learning Machines. IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics) 37:1321–1331 (2007).
32. Takagi, H., Hayashi, I. NN-driven fuzzy reasoning. International Journal of Approximate Reasoning 5:191–212 (1991).
33. Ukhurebor, K.E., Abiodun, I.C. Variation in annual rainfall data of forty years (1978-2017) for south-south, Nigeria. Journal of Applied Sciences and Environmental Management 22:511 (2018).
34. Ukhurebor, K.E., Azi, S.O., Aigbe, U.O., Onyancha, R.B., Emegha, J.O. Analyzing the uncertainties between reanalysis meteorological data and ground measured meteorological data. Measurement 165:108110 (2020).
35. Wahyuni, I., Mahmudy, W.F., Iriany, A. Rainfall prediction using hybrid adaptive neuro fuzzy inference system (ANFIS) and genetic algorithm. Journal of Telecommunication, Electronic and Computer Engineering (JTEC 2017).
36. Zarandi, M.H.F., Hadavandi, E., Turksen, I.B. A hybrid fuzzy intelligent agent-based system for stock price prediction. International Journal of Intelligent Systems 27:947–969 (2012).