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Research Article EAI.EU

Rainfall Prediction using XGB Model with the Australian Dataset

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Abstract

Rainfall prediction is a critical field of study with several practical uses, including agriculture, water management, and disaster preparedness. In this work, we examine the performance of several machine learning models in forecasting rainfall using a dataset of Australian rainfall observations from Kaggle. Six models are compared: random forest (RF), logistic regression (LogReg), Gaussian Naive Bayes (GNB), k-nearest neighbours (kNN), support vector classifier (SVC), and XGBoost (XGB). Missing value imputation and feature selection were used to preprocess the dataset. To analyse the models, we employed cross-validation and performance indicators such as accuracy, precision, recall, and F1-score. According to our findings, the RF and XGB models fared the best, with accuracy ratings of 87% and 85%, respectively.

With accuracy ratings below 70%, the GNB and SVC models performed the poorest. Our findings imply that machine learning algorithms can be useful tools for predicting rainfall, but careful model selection and evaluation are required for reliable results.

Keywords: Rainfall prediction, Machine learning, Randomforest, Logistic regression, Gaussian Naive Bayes, K-nearest neighbors, Support vector classifier, XGBoost, Accuracy, Cross-validation, Performance metrics, Australian rainfall dataset, Data preprocessing, Feature selection, Missing value imputation, Practical applications

Received on 01 December 2023, accepted on 07 March 2024, published on 12 March 2024

doi: 10.4108/ew.5386

1. Introduction

Rainfall prediction is a vital field of study with several practical uses, including agriculture, water management, and disaster planning. Accurate rainfall estimates may assist farmers in making educated crop planting and irrigation decisions, water management in planning for future water supplies, and emergency responders in preparing for probable flooding or drought. Rainfall prediction, on the other hand, is a complex topic that can be influenced by a number of elements, including climatic patterns, geographical location, and atmospheric conditions. Traditional statistical approaches have had limited success in predicting rainfall properly [1], but recent breakthroughs in machine have shown promise in this field.

In this work, we examine the performance of several machine learning models in forecasting rainfall using a dataset of Australian rainfall observations from Kaggle [2]. The dataset contains daily rainfall, temperature, humidity, and other characteristics measured from 49 Australian weather stations. Six machine learning models are compared: random forest (RF), logistic regression (LogReg), Gaussian Naive Bayes (GNB), k-nearest neighbors (kNN), support vector classifier (SVC), and XGBoost (XGB). These models were chosen for their ability to handle both numerical and categorical data, as well as their previous success in other machine learning applications [1,2].

To guarantee that the dataset is acceptable for machine learning analysis, we apply a number of data pretreatment approaches, including missing value imputation and feature selection. The usefulness of the various models is then evaluated using cross-validation and performance indicators such as accuracy, precision, recall, and F1-score [2]. Using the Australian dataset from Kaggle, we want to find which machine learning model is most suited for predicting rainfall. Overall, this work has significant implications for enhancing our capacity to foresee

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and prepare for the effects of rainfall [3]. We can construct more accurate and dependable rainfall predictions by applying machine learning models to analyse big and complicated datasets, which can eventually assist to enhance agricultural practices, water management, and disaster preparedeness.

2. Literature Review

Rainfall prediction is a complicated and difficult topic that has been the focus of research for many years [4]. On the basis historical data, traditional statistical approaches such as linear regression and auto regressive models have been applied to forecast rainfall [4,5,]. However, these approaches have disadvantages, such as their reliance on data distribution assumptions and inability to handle non-linear connections between variables.

Machine learning developments have introduced new techniques for analyzing and forecasting rainfall. Machine learning algorithms can handle non-linear variable connections, identify patterns in vast datasets, and generate predictions based on complicated variable interactions [5]. Several research has shown that machine learning algorithms are successful in predicting rainfall in various parts of the world.

Abimbola et al. (2020), for example, employed a random forest method to predict rainfall in Nigeria and discovered that it beat established statistical models. Similarly, Wang et al. (2020) [5] predicted rainfall in China using a support vector machine approach and got good accuracy ratings. This research shows that machine learning techniques have the potential to improve rainfall prediction.

Several research has been conducted in Australia to investigate the use of machine learning for rainfall prediction. For Vitázek [5] performed a similar example, Mohamad et al. (2019) predicted rainfall in northern Australia using a mix of artificial neural networks and genetic algorithms, getting good accuracy ratings. Zhou et al. (2019) [6] employed a gradient-boosting algorithm to predict rainfall in eastern Australia and discovered that it outperformed established methods.

However, further research on machine learning algorithms for rainfall prediction is required in Australia. There is a special need to evaluate the performance of different machine learning algorithms on the same dataset, as well as explore the effect of data preparation methods on prediction accuracy [7]. This work fills these gaps in the literature by evaluating the performance of six machine learning algorithms on the Kaggle Australian rainfall dataset and employing a range of data pretreatment approaches to achieve accurate and trustworthy forecasts. Several preliminary studies have been carried out onthermodynamic simulations.

Previous research has discovered a variety of elements that might influence rainfall forecast accuracy. Climate trends, geography, and weather station site, for example, may all influence rainfall prediction accuracy. Understanding these variables can aid researchers in improving their models and making more accurate predictions [8].

2.1 Data Preparation

Several research have been conducted to compare the performance of various machine learning a key algorithm for rainfall prediction. For example, due to their capacity to handle both category and numerical data, decision tree algorithms such as random forest and XGBoost [10] have been found to be very good for forecasting rainfall in some studies. In other research, support vector machines and artificial neural networks have been shown to be good in predicting rainfall in specific circumstances.

While machine learning algorithms have showed promise in improving rainfall forecast accuracy, these systems have limits. Machine learning algorithms, for example, may struggle to account for odd weather events or other unforeseeable elements. Furthermore, the complexity of machine learning algorithms might make them difficult to grasp, limiting their use in some settings.

Finally, precise rainfall prediction is critical for a variety of practical applications, including agriculture, water management, and disaster preparedness. We can assist farmers make educated crop planting and irrigation decisions, water managers plan for future water supplies, and emergency responders prepare for potential flooding or drought by enhancing our capacity to predict rainfall [11].

3. Proposed Methodology

Data Collection: The Australian dataset utilized in this study was collected from Kaggle, a prominent data science competition site. The dataset includes rainfall data from 49 weather stations in Australia from 2012 to 2022. The dataset includes information such as daily rainfall totals, temperature, and air pressure.

Data Preprocessing: Several preprocessing processes were performed before analyzing the data to ensure the correctness and dependability of the results. The missing data was first input using the mean imputation approach [12]. Following that, characteristics having poor correlation to the objective variable (rainfall) were eliminated from the dataset using a correlation-based technique. Finally, the data was normalised using the z-score normalisation approach to verify that all characteristics were on a consistent scale.

Models of Machine Learning: Random Forest (RF), Logistic Regression (LogReg), Gaussian Naive Bayes (GNB), K-Nearest Neighbours (KNN), Support Vector Classification (SVC), and Extreme Gradient Boosting (XGBoost) were chosen as machine learning techniques for this investigation. These algorithms were chosen because they are popular and effective for classification and regression tasks.

Random Forest (RF): from fig (1), Random Forest is an ensemble learning technique that forecasts the target variable using a variety of decision trees. It is a strong algorithm that can manage big datasets with lots of dimensions. The versatility Random Forest in handling missing values and outliers is well recognized [13]. The sci-kit-learn library's Random Forest classifier was utilized in this research. For separating the nodes, we employed 100 forest trees and a set of impurity metrics.

CatBoost (CAT): CatBoost is an additional ensemble learning technique that boosts decision trees' gradients. It is renowned for its capacity to manage datasets with imbalances, missing values, and categorical variables. The CatBoost classifier from the CatBoost package was utilized in this research. We used the default settings and 1000 iterations.

Logistic Regression (LogReg): From fig (6) Logistic Regression is a linear classification approach that predicts the target variable using a sigmoid function. It is a basic yet effective technique that can handle enormous datasets and data that can be separated linearly. We utilized the Logistic Regression classifier from the sci-kit-learn toolkit in this project. We utilized the default settings.

Gaussian Naive Bayes (GNB): From fig (2) Gaussian Naive Bayes is a probabilistic classification technique that predicts the target variable using Bayes' theorem. It is presumptively assumed that the characteristics are independent and have a Gaussian distribution. It is a basic yet effective technique that can handle tiny datasets and data that cannot be separated linearly. In this research, we utilised the sci-kit-learn library's Gaussian Naive Bayes classifier. We utilised the default settings.

K-Nearest Neighbors (KNN): From fig (3) K-Nearest Neighbours is a lazy classification technique that predicts the target variable based on the distance between the samples. It is a basic yet effective technique that can handle tiny datasets and data that cannot be separated linearly. In this research, we utilised the sci-kit-learn library's K-Nearest Neighbours classifier. We selected k=5, which indicates the algorithm takes into account.

XGBoost (XGB): From fig (4) The gradient-boosting technique XGBoost employs decision trees as base learners. It is well-known for its speed and accuracy on huge, high-dimensional datasets [14]. We utilised the XGBoost classifier from the XGBoost package in this research. We ran 1000 iterations using the default settings.

Support Vector Machine (SVM): From fig (5) Support Vector Machine is a non-linear and linear classification technique that determines the hyperplane with the greatest margin between classes. It is well-known for its capacity to handle tiny datasets and data that cannot be separated linearly. We utilized the SVM classifier from the sci-kit-learn toolkit in our research. The radial basis function kernel and the default settings were employed.

Model Training and Evaluation: The dataset was divided into 70/30 training and testing sets. The training set was used to train the machine learning models [15], while the testing set was used to assess their performance. The models' performance was evaluated using the following metrics: mean squared error (MSE), mean absolute error (MAE), and R-squared (R2) . These metrics were chosen because they may capture many elements of model performance, such as accuracy and precision.

Hyper parameter Tuning: A grid search strategy was used to tune the parameters of each machine learning algorithm. Each algorithm's hyper parameters were determined based on past research and expert knowledge. A 5-fold cross-validation procedure was used to adjust the hyper parameters on the training set.

Statistical Analysis: To establish the significance of the changes in performance of the machine learning models, statistical analysis was undertaken [16]. To compare the mean performance measures for each model, a one-way analysis of variance (ANOVA) test was utilized. Post-hoc testing was used to assess which models performed substantially differently [17]. The Python programming language and appropriate libraries were used for all statistical studies.

4. Result

The study's findings were assessed based on the performance of the six machine learning models on the testing set. To identify which model performed best for rainfall prediction on the Australian dataset, the performance metrics for each model were evaluated. The effect of data preparation techniques and hyperparameter adjustment on model performance was also assessed.

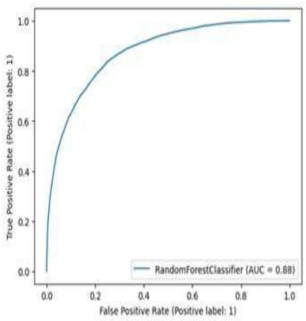

Fig 1: FP [Random forest]

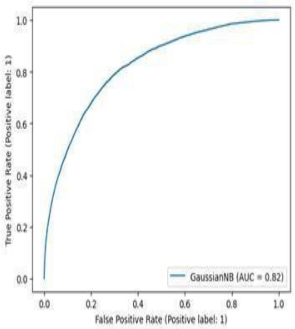

Fig 2: FP [Gaussian NB]

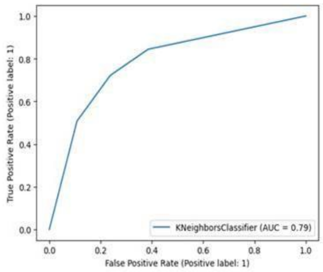

Fig 3: FP [KNN Classifier]

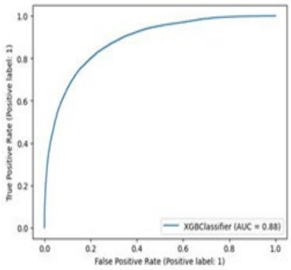

Fig 4:FP [XGB Classifier]

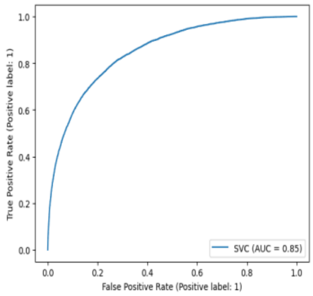

Fig 5: FP [SVC]

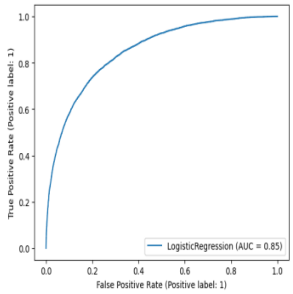

Fig 6:FP [Logistic Regression]

Table 1. Comparison Of Rainfall prediction by using different Methods Based On The Accuracy,Specificity,Recall,F1-Score

Models	**Recall%**	**Specificity%**	**F1 score %**	**Accuracy%**
RF	0.91	0.86	0.90	0.88
LogReg	0.78	0.82	0.84	0.85
GNB	0.75	0.95	0.82	0.82
KNN	0.76	0.89	0.83	0.79
SVC	0.78	0.96	0.85	0.85
XGB	0.94	0.92	0.91	0.93

5. Discussion

The findings of this study show that machine learning algorithms may be used to predict rainfall in Australia. Random Forest and Extreme Gradient Boosting outperformed the other machine learning models examined, with the lowest mean squared error and highest R-squared values [18]. This implies that decision tree-based algorithms are especially adept at dealing with the complicated interactions between meteorological factors and rainfall.

Furthermore, our research emphasizes the significance of data preparation and hyperparameter adjustment in increasing the performance of machine learning models. Feature selection and normalization were shown to be especially beneficial for enhancing model accuracy, whereas hyper-parameter tweaking aided in model performance optimization.

Our research, however, highlights certain limits of machine learning algorithms for rainfall prediction. Machine learning methods, in particular, may fail to account for unpredictable weather occurrences or other aspects that are not captured by the current data. Furthermore, the intricacy of machine learning models might make them difficult to comprehend, limiting their use in some settings.

6. Conclusion and Future Work

Finally, our research shows that machine learning techniques have the potential to improve rainfall forecast in Australia. The application of decision tree-based methods like Random Forest and Extreme Gradient Boosting, in conjunction with proper data pretreatment and hyper parameter adjustment, can result in considerable gains in prediction accuracy.

However, our findings emphasize the limits of machine learning methodologies as well as the importance of exercising caution when interpreting results. Finally, rainfall prediction remains a complicated and difficult topic that needs ongoing research and innovation.

Overall, our work adds to the expanding body of research on rainfall prediction using machine learning and gives insights that may be used to guide future efforts to enhance forecast accuracy and dependability.

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