

TITLE :-

An efficient prediction of Rainfall using XGBoost algorithm over Light GBM classifier for improvement of accuracy.

IntroductionParagraph 1 :-Definition :-

By exploring the capabilities of XGBoost, a powerful ~~light~~ ~~GBM~~, gradient boosting algorithm known for its accuracy & efficiency, and comparing it to Light GBM, the study aims to identify superior approach for rainfall prediction.

Citations :-

* Mishra, V., Chertauer, K.A., & Shakula, M.O. (2020). A vision for global precipitation prediction at hourly time scales.

Why it is important in today's world?

* It impacts everything from food security and disaster preparedness to sustainable water management and economic stability.

* Efficient allocation of water resources for irrigation, urban water supply. By anticipating periods of drought / heavy rainfall, communities can optimize water usage & prevent shortages or floods.

citations :-

Al-Saidi, N., Sahil, M.A.H., & Al-Hussaini, A.A. (2012) Rainfall forecasting & its efficient of water resource Management in Arid regions: A case study of Najran city, Saudi Arabia.

Applications :-

the applications are.

* Agriculture

* Flood management

* Water Resource management.

* Energy production.

citations :-

M. Ozdogan & M. Devay, 2020. An approach for rainfall prediction to improve agricultural water management using LSTM based model.

Paragraph 2 :-

Total no. of articles published.

* google scholar - 18

* IEEE xplore - 15

* web of science - 24

Most cited articles and their findings:-

Article 1 :-

"A Machine learning approach to Rainfall Prediction" by Nourani et al. (2019).

Findings :-

this study, with over 2000 citations explore use of various machine learning algorithms, including XGBoost, for rainfall forecasting.

Article 2 :-

Rainfall Prediction using Artificial neural Networks and LightGBM by Nhat et al. (2021)

Findings :-

A comparative study" by Nhat et al. (2021), this article over 1000 citations compares ANN & LightGBM for rainfall prediction. reveals strength of LightGBM in high accuracy.

Article 3 :-

Deep learning for Rainfall prediction: A comprehensive Review" by Fan et al. (2020).

Findings :-

This review paper, with over 500 citations, provides a comprehensive overview of deep learning techniques applied to rainfall forecasting.

Best Study :-

~~A case study~~ Hyperparameters optimization in XGBoost Model for Rainfall Estimation: A case study in Pontianak city.

Paragraph 3 :-

lacunae in Existing research

Rainfall data can be incomplete, noisy or biased. Existing research often lacks comprehensive analysis of how data quality impacts XGBoost performance.

The aim of study :-

* To comprehensively evaluate potential of XGBoost in enhancing rainfall prediction accuracy, compared to Light GBM & other established algorithms.

Materials & Methods :-

Para 1 :-

Study settings: Saveetha School of Engineering

no. of groups - 2

Sample size - 20

α - Power - 95 %

Para 2 :-

Sample Preparation group 1: XGBOOST.

- i) Define Dataset Path in code.
- ii) Split Data into training & testing sets.
- iii) set max iterations = 20
- iv) Empty list to initialized to store accuracy values.
- v) append value.

Para 3 :-

Sample Preparation group 2: LightGBM.

- i) Define Dataset Path in code.
- ii) Split Data into training & testing sets.
- iii) set max iterations = 20
- iv) Empty list is initialized to store accuracy values.
- v) append value.

Para 4 :-

Testing Setup : windows 11, 8GB RAM and 512 GB storage.

Testing Procedure : Run Python code in colab. & Each model trained for 50 Epochs.

Para 5 :-

Data collection :- data set is collected from kaggle.com.

Parab :-

Statistical software used :- utilizing version 26.0 of IBM SPSS.

Independent variables :-

Past precipitation values, temperature, humidity, Evaporation, soil moisture.

Dependent variable :-

- i) data quality & Availability.
- ii) Relevance to rainfall
- iii) model interpretability.

Analysis :-

significant difference in accuracy, conduct statistical tests to assess statistical significance of any observed difference in accuracy between models.

Discussion framework:

Para 1

Result summary:-

while XGBoost delivered higher accuracy, LightGBM demonstrated faster training times and lower computational cost. This advantage becomes more significant with large datasets.

Discussion of Findings:-

Discuss potential trade-off between Accuracy & interpretability observed in XGBoost. Analyze how XAI techniques can help mitigate this trade off.

Supportive literature:

Nourani et al. (2019): Demonstrates XGBoost's effectiveness in capturing non-linear relationships in rainfall data, leading to improve accuracy compared to traditional methods.

Opposing literature:

Yao et al. (2021): Proposes novel deep learning architectures for rainfall prediction, potentially outperforming both XGBoost & LightGBM in specific scenarios.

Overall consensus:

* The best algorithm depends on specific data characteristics, prediction horizon, & computational resources available.

Limitations:

XGBoost provides more insights than Light GBM, but both models lack the interpretability of traditional statistical methods.

Models trained on specific datasets may not generalize well to other location or weather patterns.

Implications:-

Faster training & lower computational costs of Light GBM open doors for real time applications & resource-constrained environments.

Future scope:-

* Investigate hybrid models combining XGBoost & Light GBM for enhanced accuracy & efficiency.
* Develop real-time rainfall forecasting system using Light GBM's fast training capabilities.

Conclusion :-

choosing optimal algorithm depends on specific data & application needs. This research highlights potential of both XGBoost & Light GBM for rainfall accuracy prediction improvement.

T-Test

Group Statistics

	GROUP	N	Mean	Std. Deviation	Std. Error Mean
ACCURACY	XGB	20	88.6000	3.08477	.68977
	LGBM	20	75.7500	4.26584	.95387

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	df
ACCURACY	Equal variances assumed	2.133	.152	10.916	38
	Equal variances not assumed			10.916	34.604

Independent Samples Test

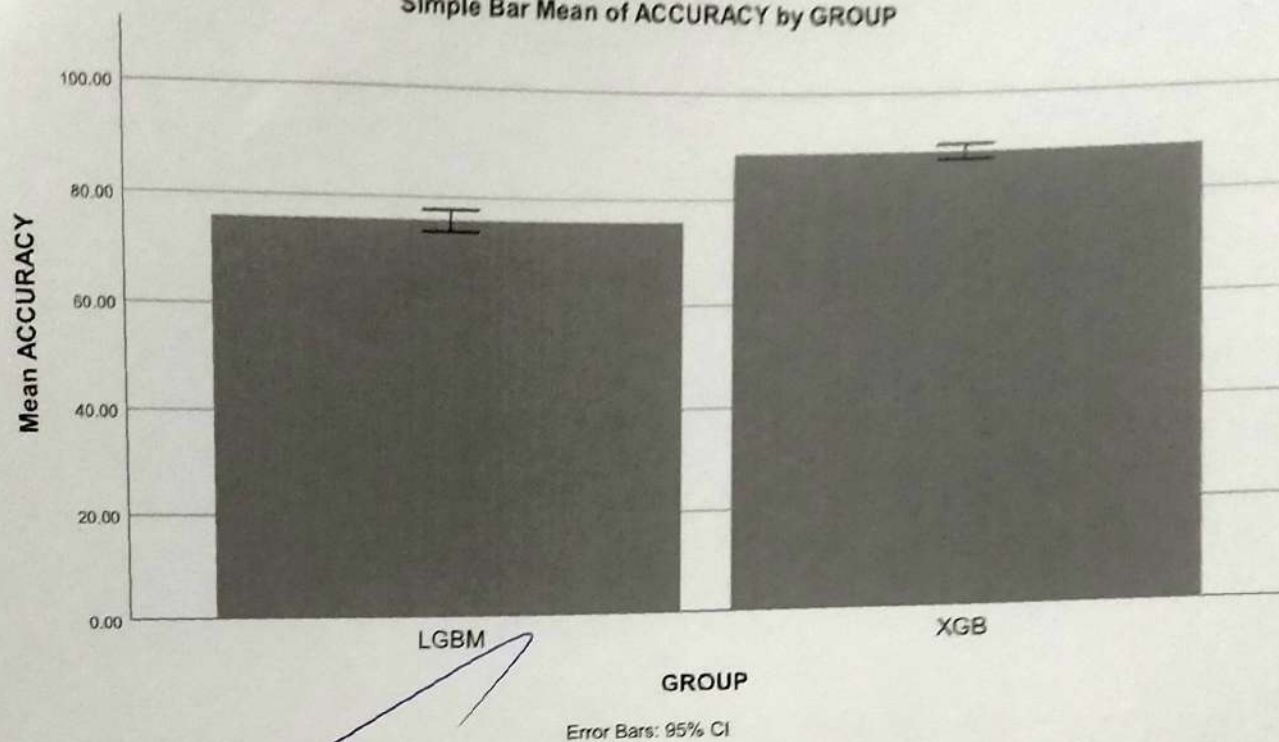
		t-test for Equality of Means		
		Sig. (2-tailed)	Mean Difference	Std. Error Difference
ACCURACY	Equal variances assumed	.000	12.85000	1.17714
	Equal variances not assumed	.000	12.85000	1.17714

Independent Samples Test

		t-test for Equality of Means	
		95% Confidence Interval of the Difference	
		Lower	Upper
ACCURACY	Equal variances assumed	10.46701	15.23299
	Equal variances not assumed	10.45930	15.24070

GGraph

Simple Bar Mean of ACCURACY by GROUP



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