すけしき

Improving efficiency of anticipating rainfall using XGBOOST in companison with logistic regression.

Introduction:

Pagagraph 1:

Detivition:-

x EnBoost PS a powerful gradient boosting algorithm, as a potential tool for imploving efficiency of sainfall prediction compared to efficiency of sainfall prediction while logistic widery used to gistic ségression. while logistic regression has long seared as teliable method for becaused rainfall prediction.

cit ations:

ozdogan, M., & Devay, M. (20%). An approach for rainfall Predictions to improve agricultural water manage ment using LSTM based Model.

why it is important in todays wood!

precise reinfall forecasts empower farmers to optimize water usage, plan planning & haguesting schedules and cultimately secure food Production for a growing global population. 2023/12/20-09:16

citations;

ozdogan, M., & Devay, M. (3030). An approach for rainfall Predictions to improve agricultural water management using 15TH based model.

Applications:-

* Energy Production

* Agricutuse

* Disaster preparedness

* wate resource management.

citations :-

Al-saidi, d., salih, M.A.M., & Al-HOSBarni, A.A (200).

Rainfall forecosting & its effect on water resource management in arts regions: A case Study of Najtan City, saudi Arabia.

Paragraph 2:-/

TOTAL number of anticles Published.

* 9,00 gle schola9 - 18

* I E E E X P/086 - 15

* web of science-25

Most cited asticles & their findings

Asticle 1:-

A madrine leagning approach to Rainfall Prediction by nousani et al. (2019).

Findings:

5

This study, with over 2200 citations, explores various machine learning algorithms, including X & BOOST for rainfall forecosting.

Axticle 2:-Extreme Enradient BOOSting for Time sonies fore casting: A case study of Rainfall Prediction. by yet al. (2020).

Findings:

It showing the superior ability of xGBOOST to capture temporal dependencies & non-linear relationships compased to simples models like 10995tic regression.

Abticle 3:

Rainfall forecasting using Hybrid Deep leagning model with Feature Engineering Techniques" by wang et al. (2022).

Eingings:-

This paper explores potential of advanced deep leagning models for rainfall prediction. This can inspire ferture research directions beyond xerboost & logistic regression.

Best study:

A combined framework for sainfall Prediction using x 6,800st & togistic regression for Feature importance Analysis" by zhang et al. (2023).

Padagraph 3:lacunae in Existing research

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

XCIBOOST PERFORMANCE. 2023/12/20 09:17

the aim of our study:
* To comprehensively evaluate potential

of x61800st in enhancing rainfall prediction accuracy. compaged to Random forest & other established algorithms.

Materials & nethods:

Para 1:

Study settings: Saveetha school of Engineeting no. of group-2 sample size-20 G- Power-95%

Para-2: Sample preparation group 1: x & Boost

- i) befine bataset Path in code.
- i) splitting that bata into training & resting.
- iii) set max iterations = 20
- iv) EMPty (ist is initialized to store accusacy
- v) append value.

Paga-3:

sample preparation group 2:- Rlogistic Regression.

ii) splitting data into training & resting sets.

iii) set max "terations = 20

iv) Enpty 1:st is initialized to store acase values.

v) append value.

Pana-M:

Testing set up: windows 11, 889B RAM & 512 GB Storage.

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

Data collection: - Data is collected from raggle-com.

Para b: Statistical software used: utilizing version 26.0 of IBM spss.

Independent variables: Humidity, Temperature, soil moisture, ctoud carg.

Dependent vaniables:-?) Data Availability & quality.

ii) Relevance to sainfall

iii) model interpretability.

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come

Analysis:

significant differences in accuracy,

conduct statistical tests to access

statistical significance of any observed

differences in accuracy between models.

ois cussion frame work:

basar;

Result Summary:
while xer Boost deliver higher accuracy, bugget while xer Boost deliver higher accuracy, bugget while xer Boost deliver higher accuracy, bugget 10 gistic regression demonstrated faster training to gistic regression demonstrated faster training to yellower computational cost.

Discussion of Findings:

Discussion Potential trade off between Accuracy & interpretability observed in Xon-Boost. Awayze how XAI rechniques can here Mitigate this trade-off.

supportive literature:

Nourani et al (2019): Demonstrates xorboosts

effectiveness in capturing non-linear relationships

in rainfall data, leading to improve accusary

compared to traditional methods.

y a o et a 1. (2021) proposes novel deep leagning architecture for rainfall prediction, potentiary

performing both x G1800st & LightG184 in specific scenarios.

* The best algorithm depends on specific days.

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Characteristics & confutational resonaces

available.

Linitations:

x& Boost Provides more insights than logistic regression but both models lack interpretability of traditional statistical methods.

IMPlications:

Forster training & lower computational costs.

of light GBH open doors for real time
applications & regarder constrained environments.

Future scope:

* Investigate hybrid models combining XGIBOOST & was logistic regression for enhanced accuracy and efficient.

conclusion:

choosing optimal algorithm defends on specific data & application needs. This research highlight potential of both xerboost & logistic regression for rainfall accustacy prediction pullovemero23/12/2009:27

T-Test

Group Statistics

	GROUP	N	Mean	Std. Deviation	Std. Error Mean
ACCURACY	XGB	20	0 96.3500 1.63111	1.63111	.36473
	LR	20	87.6000	4.45327	.99578

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	df
Equal variar	Equal variances assumed	33.502	.000	8.251	38
	Equal variances not assumed	Car department		8.251	24.008

Independent Samples Test

t-test	for	Fal	ville	of	M	69	ns

	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Equal variances assumed	.000	8.75000	1.06047
Equal variances not	.000	8.75000	1.06047
	Equal variances not	Equal variances assumed	Sig. (2-tailed) Difference Equal variances assumed .000 8.75000 Equal variances not .000 8.75000

Independent Samples Test

t-test for Equality of Means

95% Confidence Interval of the

		Difference	
		Lower	Upper
ACCURACY	Equal variances assumed	6.60318	10.89682
	Equal variances not assumed	6.56133	10.93867

GGraph

