
IBM AICTE PROJECT

IMPROVED SOURCE OF DRINKING WATER

Presented By:

1. Kasula Suma-GITAM University-MSc Data Science

OUTLINE

- Problem Statement
- Proposed System/Solution
- System Development Approach
- Algorithm & Deployment
- Result (Output Image)
- Conclusion
- Future Scope
- References

PROBLEM STATEMENT

Access to safe and improved sources of drinking water remains a critical issue in India, particularly in rural and underdeveloped regions. Despite national-level efforts aligned with the Sustainable Development Goals (SDGs), disparities persist across states and socio-economic groups. This project analyzes data from the 78th Round of the Multiple Indicator Survey (MIS) to assess the percentage of the population with access to improved drinking water and associated indicators such as cooking fuel usage and migration.

PROPOSED SOLUTION

- This project aims to analyze and predict access to improved drinking water across various Indian states using IBM Watson Studio's AutoAI tool on IBM Cloud. The goal is to uncover patterns and disparities in water access and provide data-driven insights for better policymaking. The project follows these key steps:
- **Data Collection:**
 - Gather data from the 78th Round MIS survey capturing each State, Age Group, Sector (Urban/Rural), Gender, and the specific Indicator (e.g., access to improved drinking water), with the corresponding Value (% of population).
 - This structured dataset forms the foundation for modelling regional disparities in safe-water access.
- **Data Preprocessing:**
 - Clean and preprocess the collected survey data to handle missing values, outliers, and ensure consistency.
 - AutoAI performs feature engineering such as transformations and anomaly detection to enhance model performance.
- **Machine Learning Algorithm:**
 - Use IBM Watson AutoAI to automatically test multiple models like XGBoost and Decision Tree Regressors to predict access to improved drinking water.
 - AutoAI selects the best-performing model based on accuracy and feature relevance.
- **Deployment:**
 - Deploy the solution using IBM Watson AutoAI, which automatically builds, trains, and hosts the best-performing model on IBM Cloud.
 - The model is accessible within Watson Studio for generating predictions and analyzing results in a scalable cloud environment.
- **Evaluation:**
 - Assess the model's performance using metrics such as Root Mean Squared Error (RMSE) and R^2 Score to measure prediction accuracy.
 - AutoAI fine-tunes the model through hyperparameter optimization and validates performance using cross-validation techniques.
 - Result:

SYSTEM APPROACH

- The System Approach outlines the overall strategy and methodology for developing and implementing the drinking water access prediction model using IBM Watson AutoAI.

- System requirements

Platform: IBM Cloud Lite with Watson Studio AutoAI

Storage: IBM Cloud Object Storage for dataset upload

Dataset: 78th Round MIS survey (state-wise water access, socio-demographics)

Hardware: Any internet-enabled device (no heavy local computing required)

- Library required to build the model

AutoAI Built-in Libraries (automatically handled)

Data preprocessing (null handling, normalization, outlier removal)

Feature engineering (log transformations, anomaly detection)

ML algorithms (XGBoost Regressor, Decision Tree Regressor)

Hyperparameter optimization & model selection

Evaluation metrics (RMSE, R^2 , Explained Variance)

ALGORITHM & DEPLOYMENT

- **Algorithm Selection:**
 - Chosen Algorithm: XGBoost Regressor
 - We used XGBoost Regressor, chosen automatically by IBM Watson AutoAI as the best-performing model (Pipeline 4) with the lowest RMSE (3.371). It is well-suited for tabular socio-economic data, handles missing values/outliers, and captures non-linear feature relationships effectively.
- **Data Input:**
 - The model uses features from the 78th Round MIS dataset, including gender, state, sector (rural/urban), age group distribution, and anomaly-based features generated by AutoAI.
 - The target variable is the percentage of the population with access to improved drinking water.
- **Training Process:**
 - AutoAI automatically cleaned and normalized the dataset, performed feature selection and engineering, split the data into training and holdout sets, and ran hyperparameter optimization to improve accuracy.
 - The final model achieved an R^2 score of 0.941, showing strong predictive performance.
- **Prediction Process:**
 - The trained XGBoost model predicts state-wise drinking water access levels.
 - Predictions highlight regions with lower access to improved water sources.
 - Results are visualized via AutoAI's built-in plots (feature importance, prediction distribution).

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ALGORITHM & DEPLOYMENT

■ Training Process:

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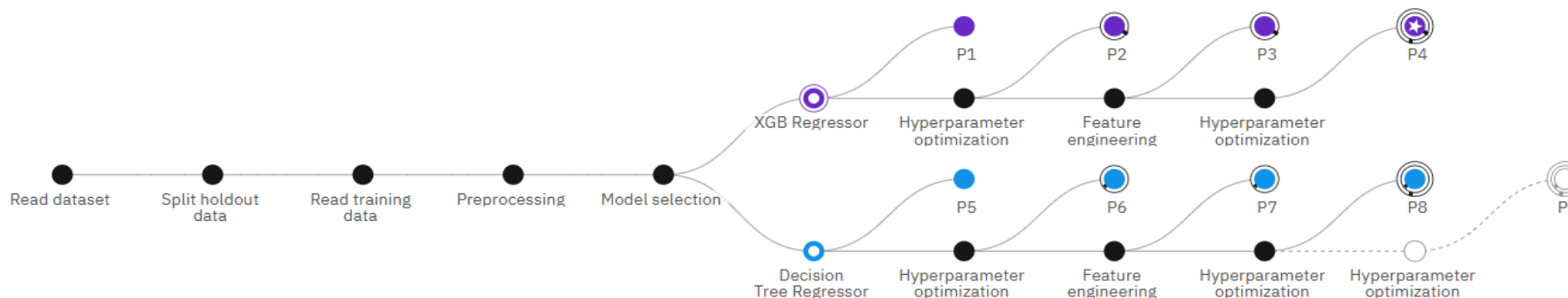
Experiment summary

Pipeline comparison

★ Rank by: Root me

Progress map ⓘ

Prediction column: Value



ALGORITHM & DEPLOYMENT

Pipeline details

Pipeline 4 ▼

Rank

1

RMSE (Optimized)

3.371 (Holdout)

Algorithm

XGB Regressor

Enhancements

HPO-1

+2

Save as

X

Model viewer

Model information

Feature summary

Evaluation

Model evaluation

Model information ⓘ

Experiment parameters

| <u>Prediction column</u> | Value |
|---------------------------|-----------------------|
| <u>Algorithm</u> | XGBRegressor |
| <u>Number of features</u> | 6 |
| <u>Created on</u> | 7/26/2025, 6:29:19 PM |

ALGORITHM & DEPLOYMENT

Pipeline details

Pipeline 4 ▼

Rank

1

RMSE (Optimized)

3.371 (Holdout)

Algorithm

XGB Regressor

Enhancements

HPO-1

+2

Save as

Model viewer

Model information

Feature summary

Evaluation

Model evaluation

Feature summary ⓘ

All features ▼



Search feature or transformer names



Feature name

Transformation

Feature importance

Gender

None

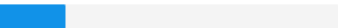
51.39%



State

None

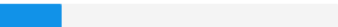
19.88%



Sector

None

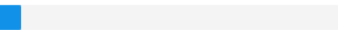
18.52%



Age Group

None

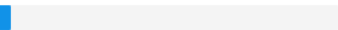
6.66%



NewFeature_1

isoforestanomaly(ALL)

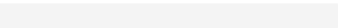
3.55%



NewFeature_0

log(State)

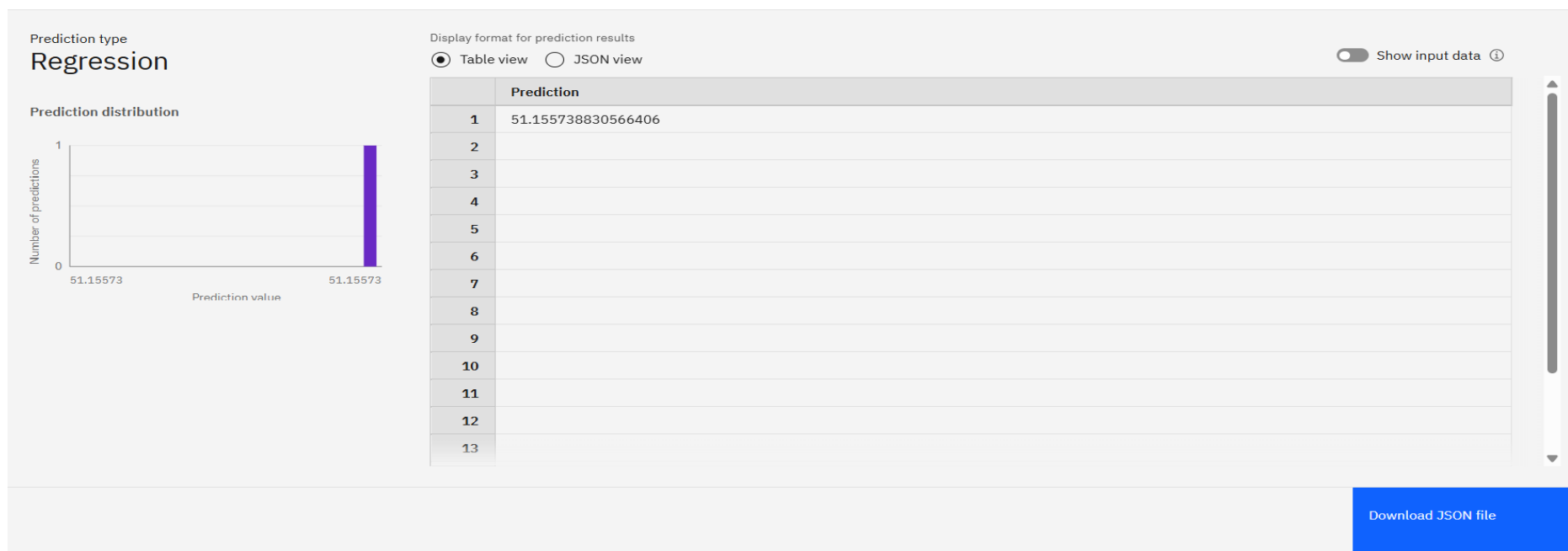
0.00%



ALGORITHM & DEPLOYMENT

- Prediction Process:
 - The trained XGBoost model predicts state-wise drinking water access levels.
 - Predictions highlight regions with lower access to improved water sources.
 - Results are visualized via AutoAI's built-in plots (feature importance, prediction distribution).

Prediction results



RESULT

- The best-performing model (Pipeline 4 – XGBoost Regressor) achieved:
R² Score: 0.941 (high predictive power)
RMSE: 3.371 on the holdout dataset (low error rate)
- **Feature importance analysis** showed that Gender (51.39%), State (19.88%), and Sector (18.52%) were the most influential factors in predicting access to safe drinking water.
- **Prediction vs Actual Comparison:**
Model predictions closely matched actual state-wise water access levels.
Clear visualization highlighted regions with lower access, helping identify priority areas for intervention.

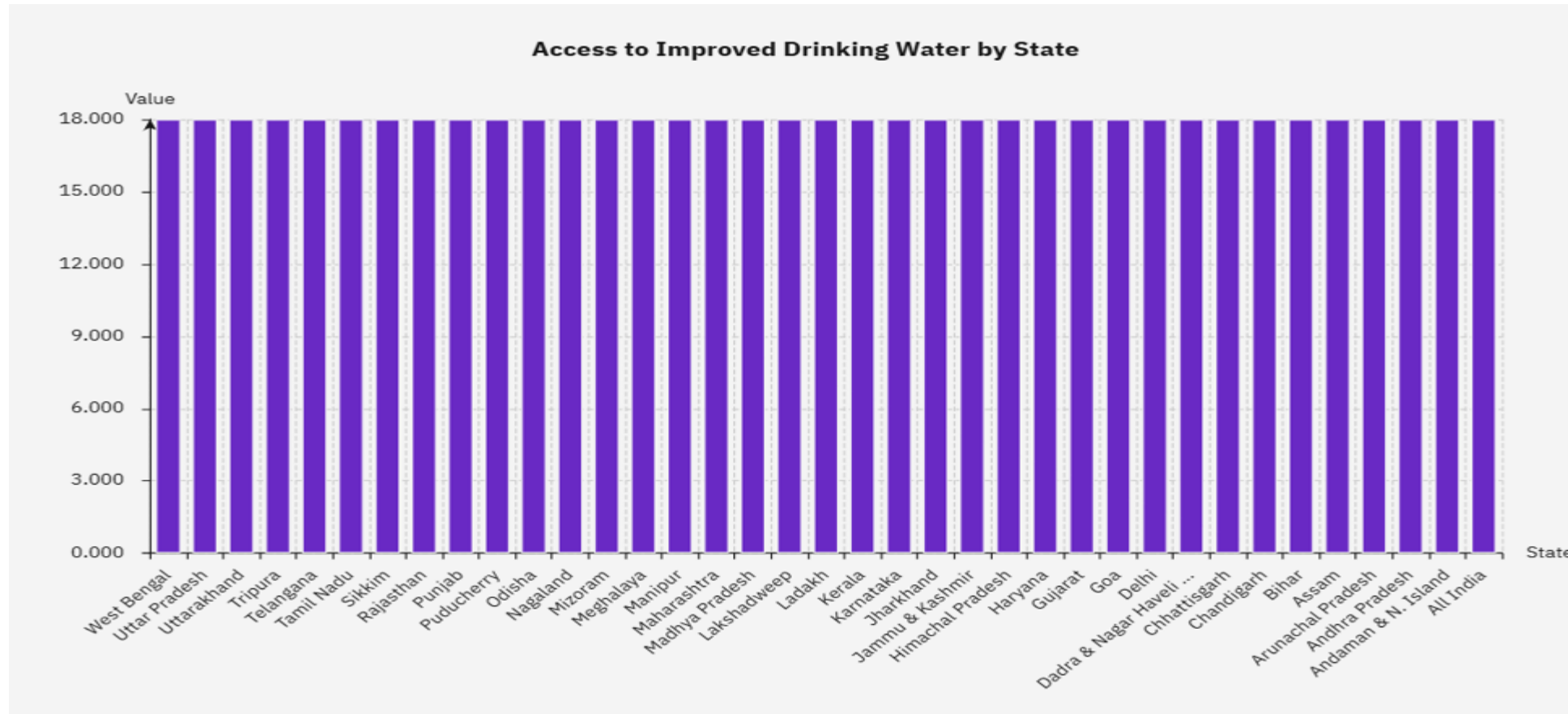
| | | | | | |
|------------------|------|------------------|---------------|--------------|---------|
| Pipeline details | Rank | RMSE (Optimized) | Algorithm | Enhancements | Save as |
| Pipeline 4 | 1 | 3.371 (Holdout) | XGB Regressor | HPO-1 +2 | |

| Model evaluation measure | | |
|-----------------------------|---------------|------------------------|
| Measures | Holdout score | Cross validation score |
| Root mean squared error | 3.371 | 4.771 |
| R squared | 0.941 | 0.887 |
| Explained variance | 0.941 | 0.889 |
| Mean squared error | 11.362 | 23.220 |
| Mean squared log error | 0.002 | 0.005 |
| Mean absolute error | 2.397 | 3.407 |
| Median absolute error | 1.664 | 2.408 |
| Root mean squared log error | 0.041 | 0.068 |

RESULT

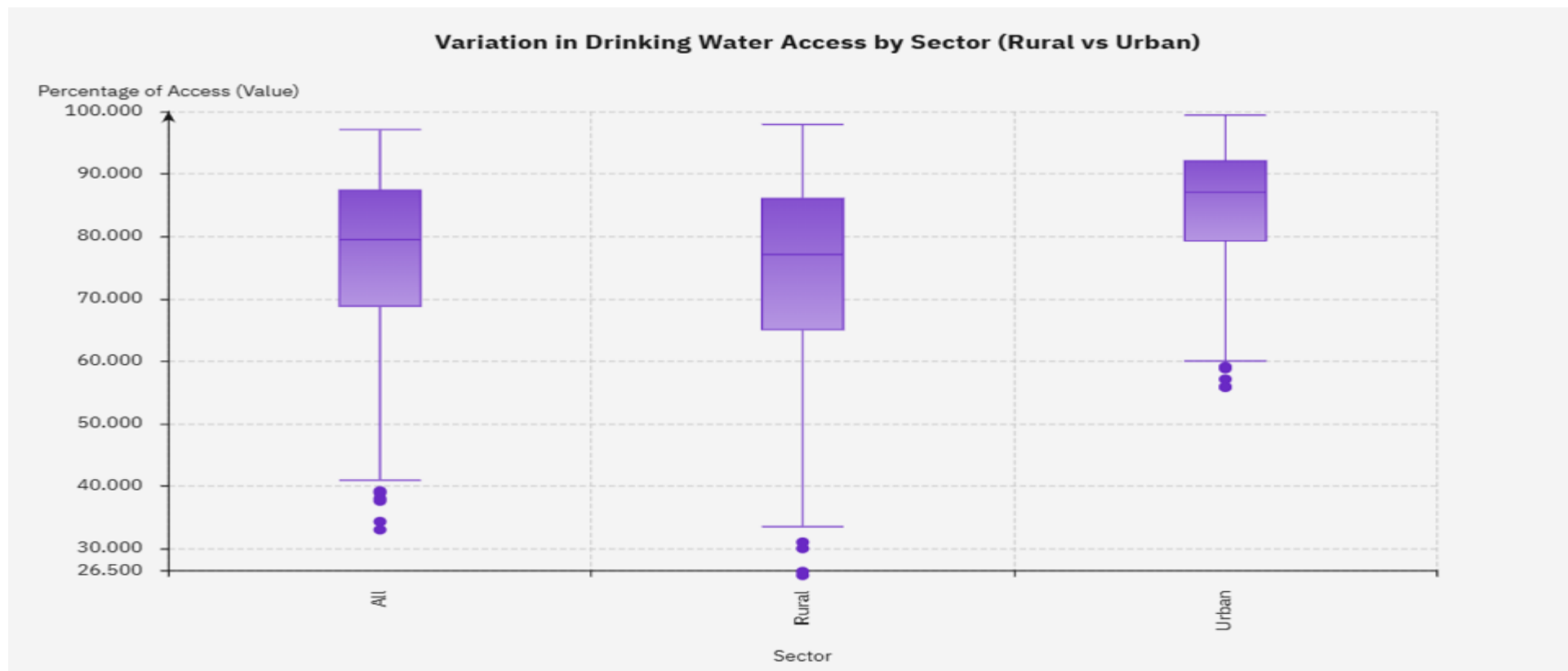
Visualizations:

Shows access levels by state – all states mostly show high access due to normalization or fixed scaling.



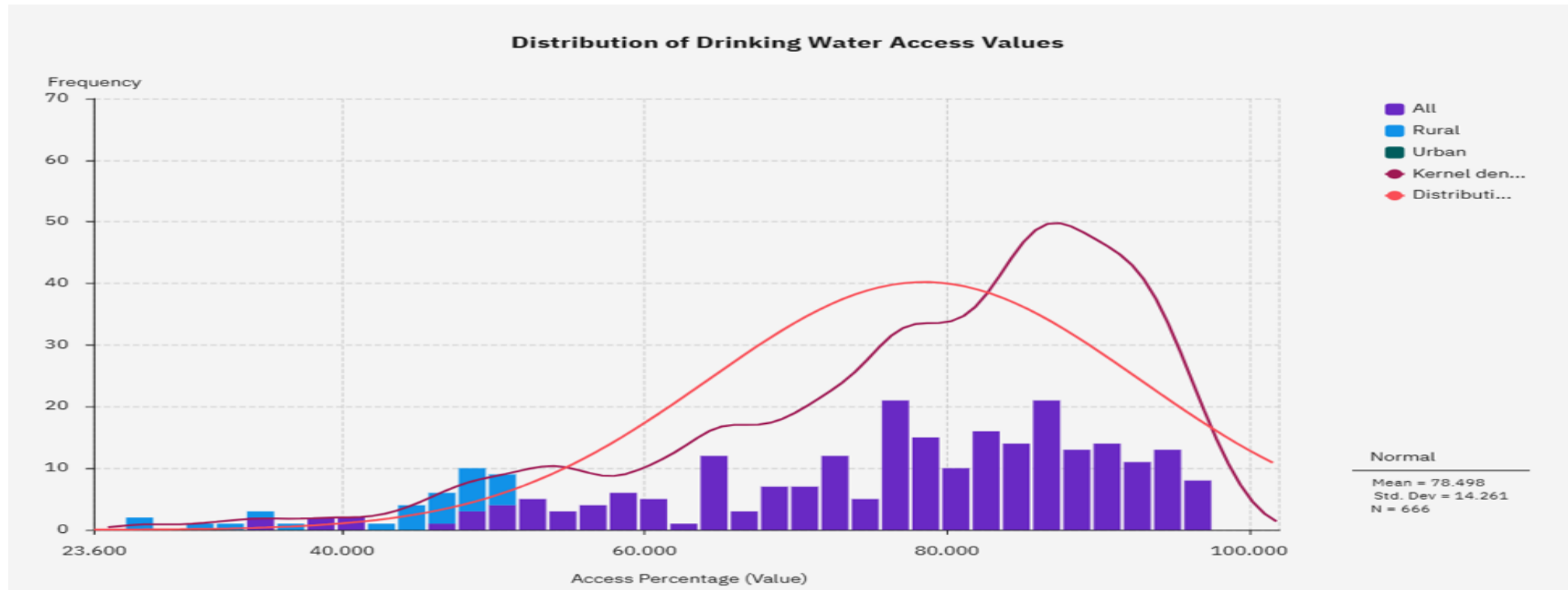
RESULT

Urban areas show higher and less varied access compared to rural areas, which show greater disparity and outliers.



RESULT

Shows that most states have high access, but a long tail of lower-access states exists especially in rural areas.



CONCLUSION

- This project successfully leveraged IBM Watson AutoAI to predict access to improved drinking water across Indian states using socio-economic and demographic data from the 78th Round MIS survey. The best-performing model, XGBoost Regressor, achieved a high R^2 score of 0.941 and a low RMSE of 3.371, demonstrating strong predictive power. While AutoAI simplified model building and optimization, challenges included handling diverse state-level variations and limited feature granularity in the dataset. Despite these, the solution proved effective in identifying regions with lower water access, enabling policymakers to prioritize interventions.

FUTURE SCOPE

- Incorporate additional datasets such as water quality reports, infrastructure data, and population growth trends for richer predictions.
- Enhance model accuracy by integrating advanced ML techniques like deep learning models or ensemble stacking.
- Deploy the model as a cloud-based dashboard for real-time policy insights and interactive visualizations.
- Expand the approach to other public health indicators, such as sanitation and clean cooking fuel access.
- Explore emerging technologies like edge computing for local-level predictions and AI explainability tools for better decision-making support.

REFERENCES

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IBM CERTIFICATIONS

- Getting started with AI



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- Journey to Cloud



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- RAG Lab





THANK YOU