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# Geo AI for Predicting Utility Asset Failures in Electric Networks: A Machine Learning Approach Using Geospatial and Environmental Data

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***Abstract:** The paper discusses the research that explored the power of Geo AI for correctly predicting asset failures in any type of utility network. Electric utility, gas utility, or water utility is highly vulnerable to environmental distress such as heavy rain or rising temperature. Traditional reactive approaches of maintenance, inspection, and rectification lead to service disruptions, and in today's day and age it is almost impossible to do something productive without a power supply. My research presents a machine learning-based approach for proactively predicting equipment failure by integrating spatial data analysis and machine learning. Study area is Odisha, which is very prone to cyclones, low depression, and rising temperatures. An electric file geodatabase was created using ArcGIS Pro and ArcPy in which real-world asset configuration was simulated. Environmental attributes like temperature and rainfall were also added using zonal statistics. This research shows how Geo AI and machine learning can be effectively used to derive preventive maintenance techniques in utility networks. The proposed project is easy to implement and cost-effective and can be viewed as a prototype for integrating predictive modeling into a GIS-based utility management system.*

***Keywords:** Geo AI, Machine Learning, GIS, Utility Network, ArcGIS Pro, ArcPy.*

## I. INTRODUCTION

In recent times, the reliability of utility networks has become increasingly critical due to rapidly growing energy demand in each sector, aging infrastructure, and the rising trend of extremity in weather events. Specifically for natural calamity-prone areas, unexpected component failure, like a disconnected conductor, pole collapse, or transformer outage, can disrupt service, increase maintenance costs, and create safety risks to both utility workers and the public. As we all know, we follow traditional schedule-based maintenance and safety check strategies, which lack spatial intelligence and data-driven insights required to predict and prevent such failures proactively. With the advent of artificial intelligence and Geographic Information System (GIS), new technologies have emerged for predictive maintenance through geospatial analysis and machine learning. The amalgam of GIS and AI is known as Geo AI, which enables utilities to use large volumes of geospatial, environmental, and operational data to identify patterns, detect risks, and optimize utility maintenance and operation. By analysing satellite-captured raster data, we can derive variables such as Normalized Difference Vegetation Index (NDVI), temperature, rainfall, and topography. Utility provider industries can gather data such as asset group, asset type, asset age, and location and then develop intelligent models that prioritize high-risk assets for inspection and repair or replacement. Despite the potential of Geo AI, one significant challenge is the unavailability of geodatabases with utility networks and features with proper attributes. This may be due to lack of survey, lack of documentation, or confidentiality. In this research I have addressed the shortcomings of data unavailability by simulating failure scenarios based on expert-informed assumptions and publicly available environmental databases. The main objective of this research is to demonstrate the feasibility of using ML models such as Random Forest, CatBoost, Naïve Bayes, and KNN for proactively predicting failures of utility network equipment using both spatial and non-spatial features.

This research paper demonstrates a case study based on an electric utility network in Odisha, India, using data derived from satellite pictures, remote sensing sources, and file geodatabase. The spatial data has been preprocessed by using the Arcpy library, and the machine learning pipeline has been developed through Python. Machine learning-related work has been done using Jupyter Notebook, and data visualization has been performed in ArcGIS Pro. The results reveal significant predictors of asset failures and generate a feature class with features having attributes like actual status and predicted status that can support preventive maintenance decision-making.

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The threefold contributions of this study are

1) To develop a Geo AI-based framework for utility component failure prediction
2) To integrate ArcPy-based spatial pre-processing with environment and asset data
3) To display a scalable, ML-driven risk model applicable to real-world electric utility networks.

## II. LITERATURE REVIEW

The rapid digitization of electric utility networks has fueled the need for intelligent maintenance strategies that can minimize asset failure risks and optimize service reliability. Traditionally, utilities relied on corrective or preventive maintenance practices driven by fixed schedules or manual inspections. However, such approaches lack responsiveness to real-time environmental changes and do not prioritize assets based on risk, often leading to avoidable failures and increased operational costs.

### *A. Asset failure prediction in electric utilities*

Numerous studies have explored failure prediction in electric utilities, primarily focusing on transformer breakdowns, conductor faults, and pole deterioration. Most of the developed models generally use non-spatial features (called as attributes of features in GIS) such as age, loading history, and voltage levels. For instance, Huang et al. [2019] applied logistic regression to predict transformer failures based on operational parameters, while Patel & Shah [2020] used decision trees to identify fault-prone conductors. Although these models offer valuable insights, they overlook spatial context, a crucial factor in infrastructure degradation.

### *B. GIS in Utility Network analysis*

Geographic Information Systems (GIS) have become foundational in modeling and managing utility infrastructure due to their efficiency in handling all operations. GIS allows utilities to maintain geodatabases of their assets, analyse connectivity like containment, junction edge connectivity, and structural attachment, and support spatial decision-making. Platforms like ESRI ArcGIS Utility Network provide tools for tracing circuits, managing associations, and visualizing asset relationships. However, most GIS-based tools are reactive, lacking predictive intelligence for failure detection or prioritization.

### *C. Emergence of Geo AI*

The emergence of GIS and artificial intelligence, known as Geo AI, has opened new frontiers in spatial data science. GeoAI enables spatially aware machine learning models that incorporate geographic patterns, remote sensing imagery, and environmental conditions. Applications of GeoAI have been reported in land cover classification, flood risk mapping, urban heat island detection, and road safety analysis. For example, [Li et al., 2021] applied convolutional neural networks to detect damaged roads using satellite imagery, while [Jha et al., 2022] used random forests and NDVI to assess crop health. Despite these advancements, GeoAI remains underutilized in utility asset failure prediction, especially for electric networks. Most existing studies either ignore spatial-environmental variables or lack integration with operational GIS platforms like ArcGIS and QGIS.

### *D. Machine Learning for Infrastructure Risk Assessment*

Machine learning (ML) models such as Random Forest (RF), XGBoost, and Support Vector Machines (SVM) have demonstrated high performance in various risk assessment tasks. These models can handle non-linear relationships, noisy data, and high-dimensional features, making them suitable for asset failure prediction. Studies in transportation, water infrastructure, and building inspection have shown that combining ML with spatial features significantly improves predictive performance. In the electric utility domain, ML has mostly been applied for load forecasting, fault classification, or energy theft detection. The application of ML for geospatially informed asset failure risk modeling is still in its infancy.

### *E. Research gap and contribution*

The literature reveals a clear gap: no existing framework fully integrates GIS-based asset management, environmental data, and machine learning to proactively predict utility asset failures. This study bridges that gap by

1) Developing a Geo AI-based failure prediction framework using ArcPy and machine learning.
2) Integrating geospatial and environmental variables (NDVI, rainfall, temperature, distance from substations).
3) Simulating failure labels in the absence of real-world logs to test model feasibility.
4) Applying the approach to an electric utility network in India using real GIS data.

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## III. METHOD

### A. Research question

Electric utility networks are critical infrastructure systems that must operate reliably under varying environmental and operational conditions. In regions like Odisha, India—where frequent cyclones, heatwaves, and heavy rainfall occur—these networks are particularly vulnerable to failures in assets such as transformers, conductors, and junction poles. Traditional maintenance and inspection methods are often reactive and resource-intensive, leading to service disruptions, increased costs, and safety risks. Recent advancements in Geo AI (geospatial artificial intelligence) have opened new possibilities for predictive maintenance by integrating geospatial data, environmental parameters, and machine learning (ML) techniques. However, challenges remain in generating realistic utility datasets, selecting meaningful predictive features, and validating model performance in diverse geographic contexts. The above-mentioned question was modified and posed in this study in the following way. Can machine learning models, when combined with geospatial and environmental data, accurately predict failures in electric utility assets?

### B. Study area and Data

This study focuses on the Indian state of Odisha, situated along the eastern coastline between latitudes 17.5°N and 22.5°N and longitudes 81.5°E to 87.5°E. Odisha's tropical climate, high monsoon variability, and vulnerability to cyclones make it a critical region for assessing the resilience and failure patterns of electric utility infrastructure. The diverse geographic and climatic profile enables a realistic simulation of asset-environment interactions for Geo AI modelling.

#### 1) Synthetic Utility Network Geodatabase

To overcome the lack of publicly accessible granular utility asset data, a synthetic utility network was generated using ArcGIS Pro and ArcPy. A file geodatabase named Odisha_GeoAI.gdb was created and structured to represent a simplified but realistic electric distribution system. The database consists of the following core feature classes:

*a)* Electric Line – Modelled as polyline features to represent overhead and underground conductors.
*b)* Electric Device – Point features representing utility devices like transformers and switches.
*c)* Electric Junction – Point features representing structural support elements such as poles.

Each feature class includes critical attributes necessary for failure prediction, such as

- assetgroup: a coded domain representing asset grouping (e.g., Primary Line, Transformer)
- assettype: a coded domain describing asset subtype (e.g., overhead, pad-mounted Transformer)
- status: the current condition of the asset (working or faulty)
- installyear: year the asset was deployed
- rainfall and temperature: environmental context values
- asset_age: derived from install year to reflect operational duration

A total of 3000 synthetic asset records were inserted (1000 per feature class) with randomized, yet nearest to real world situation, values for each attribute.

#### 2) Domain-Controlled Attribute Scheme

To imitate real-world GIS scenarios, coded value domains were implemented across all feature classes. This approach ensures standardized classification of asset group and asset type values for machine learning processing.

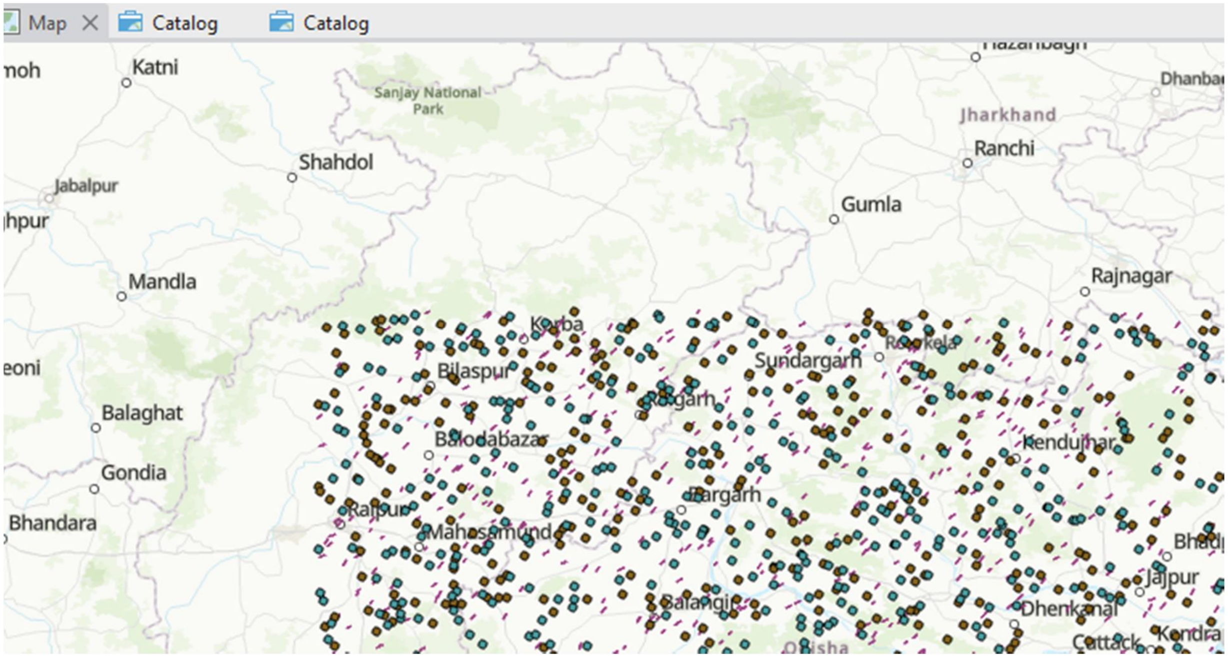
Domain mappings include:
Electric Line_AG: {1: "Primary Line", 2: "Secondary Line"}
Electric Line_AT: {11: "Overhead", 12: "Underground"}
Electric Device_AG: {3: "Transformer", 4: "Switch"}
Electric Device_AT: {21: "Pad-mounted Transformer", 22: "Pole-mounted Switch"}
Electric Junction_AG: {5: "Junction Pole"}
Electric Junction_AT: {31: "Support Structure"}
This coded schema facilitates consistent interpretation of categorical variables in the modelling phase.

#### 3) Environmental Attributes Integration

Two environmental parameters were manually simulated and assigned to each asset:

*a)* Rainfall (in mm): ranging from 800–1800 mm, based on Odisha's monsoonal variation.
*b)* Temperature (in °C): ranging from 24–42°C, reflecting seasonal extremes.

In operational deployment, these values can be extracted using spatial zonal statistics with satellite-derived raster datasets such as CHIRPS (rainfall) or MODIS (land surface temperature). For instance, ZonalStatisticsAsTable in ArcPy can be used to spatially associate environmental conditions with vector assets.




*C. Data Preprocessing*

Using table to table conversion, information each feature class (line,device,junction) was exported to a csv file. Data preprocessing, data manipulation and cleaning was done using library such Pandas and NumPy. The three datasets were concatenated into one using pd.concat(). The derived feature asset_age was added to by subtracting install year from current year. The target variable status was encoded into binary format (0 = working, 1 = Faulty) using label encoder. For creating model, we have used features like assetgroup, assettype, asset_age, rainfall and temperature.

*D. Machine learning classification*

The given dataset was split using 80-20 train test ratio with train_test_split. I have used four algorithms to train my model. Scikit learning was also used for dimensionality reduction

*1)* Random Forst
*2)* Cat Boost
*3)* K-NearesT Neighbors
*4)* Naïve Bayes

Each model was evaluated using

*a)* Accuracy Score
*b)* Classification Report (Precision, Recall, F1-Score)
*c)* Confusion Matrix
*d)* ROC Curve & AUC Curve

*E. Feature Importance Analysis*

Feature importance was extracted for each model that supported it (Random Forest and Cat Boost). This identified key predictors influencing asset failures, such as:

*1)* Asset age
*2)* Temperature
*3)* Rainfall

These insights help in proactive asset management and environmental risk assessment.

### F. *Prediction Map Generation in ArcGIS Pro*

To visualize predicted asset statuses:

1) The test dataset OBJECTIDs and predictions were saved to predictions.csv.
2) This file was imported back into the GDB using Table to table conversion.
3) A join was performed between the prediction table and Electric Line on OBJECTID.
4) The result was exported as a new feature class: ElectricLine_Predicted, symbolized by predicted status.

This enabled a spatial view of where potential asset failures are predicted to occur.

## IV. RESULTS

This section presents the outcomes of the machine learning experiments conducted on the simulated utility asset dataset. The evaluation includes classification performance metrics, feature importance rankings and spatial visualization of predicted asset failures.

### A. *Model Performance comparison*

Four classification algorithms were trained and tested using the combined dataset of 3000 records (1000 each for lines, devices, and junctions). The models were evaluated on a 20% test set (600 records), with class balance maintained between “Working” and “Faulty” statuses.

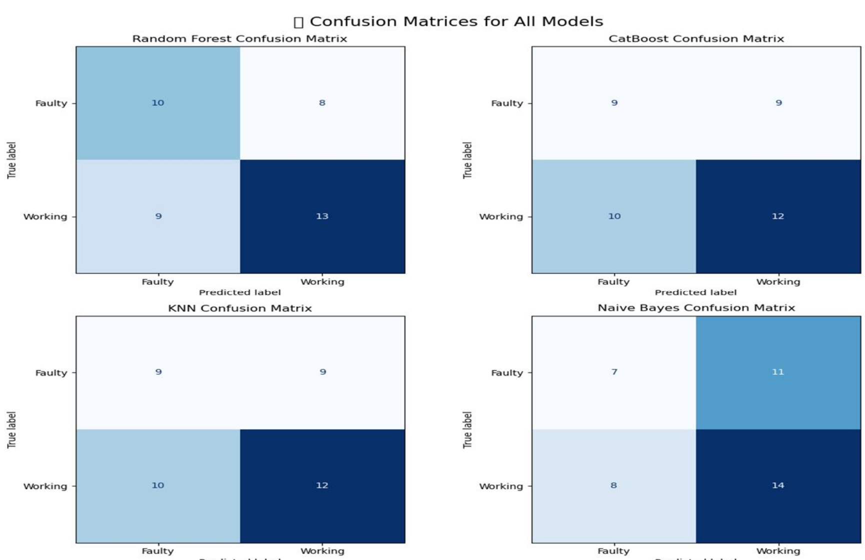
The performance metrics—accuracy, precision, recall, and F1-score—are summarized below:

| Model | Accuracy | Precision(Faulty) | Recall(Faulty) | F1-Score(Faulty) |
|---|---|---|---|---|
| Radom Forest | 0.57 | 0.53 | 0.56 | 0.54 |
| Cat Boost | 0.53 | 0.47 | 0.50 | 0.49 |
| KNN | 0.53 | 0.47 | 0.50 | 0.49 |
| Naïve Bayes | 0.53 | 0.47 | 0.39 | 0.42 |

 Insight: Random Forest outperformed the other models in all key metrics, demonstrating better ability to capture nonlinear patterns and environmental interactions.

### B. *Confusion Matrix Analysis*

The confusion matrix helps evaluate how well the models distinguish between Faulty and Working assets. A confusion matrix is a table that summarizes the performance of a classification model. It shows how well the model predicted the actual values by comparing predicted labels against actual labels. It's a crucial tool for evaluating the accuracy and identifying areas where the model is making errors.




 Insight: This matrix shows a relatively balanced classification but also highlights room for improvement, especially in reducing false negatives (failing to detect a faulty asset).

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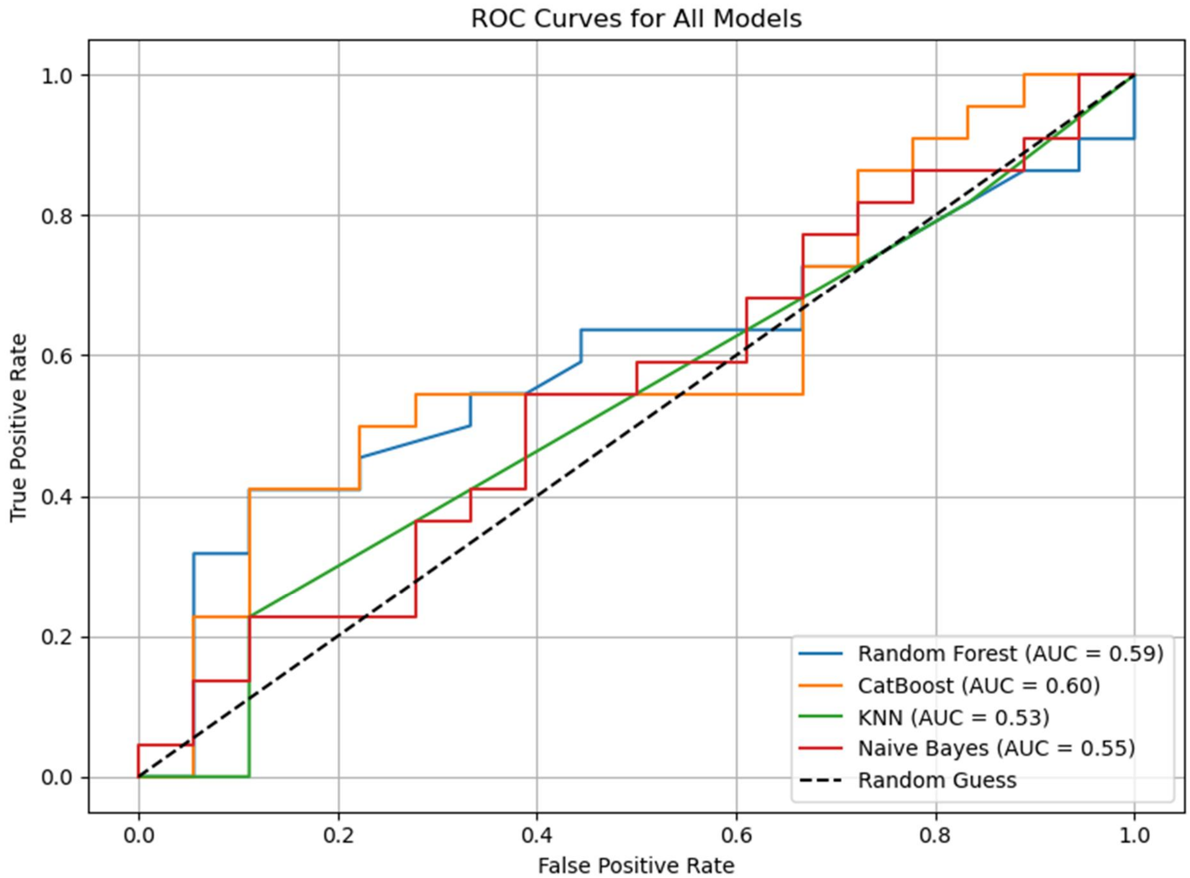
### *C. ROC Curve and AUC Curve*

Receiver Operating Characteristic (ROC) curves were plotted for all models. The Area Under the Curve (AUC) values provide a single score summarizing model performance across all thresholds. The ROC curve visually represents a model's ability to distinguish between classes at various threshold settings, while the AUC quantifies this discriminatory power.




 Insight: The ROC curve for Random Forest showed the greatest separation from the random guess line, reinforcing its comparative advantage.

### *D. Feature Importance Ranking*

Feature importance scores, extracted from Random Forest and CatBoost, reveal the most influential predictors of asset failure. Feature importance refers to techniques used in machine learning to assess the relevance of each input feature in a model's predictions. Essentially, it quantifies how much each feature contributes to the model's ability to accurately predict the target variable.

Top 3 Important Features (Random Forest):

*1)* Asset Age – Older assets show higher failure probabilities.
*2)* Temperature – High heat exposure contributes to degradation.
*3)* Rainfall – Heavy rainfall affects grounding and corrosion risk.

These results align with real-world patterns observed in electric utility infrastructure degradation.

### *E. Spatial Prediction Map in ArcGis Pro*

The final machine learning predictions were exported to a CSV and joined to the original ElectricLine feature class to produce a spatially enabled ElectricLine_Predicted layer.

*1)* Assets predicted as “Faulty” were symbolized in red.
*2)* Assets predicted as “Working” appeared in green.

PredictedTable ElectricLine_Predicted

Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear Delete Copy

| | OBJECTID * | Shape * | assetgroup | assettype | status | installyear | rainfall | temperature | OBJECTID | assetgroup | assettype | asset_age | rainfall | temperature | Actual_Status | Predicted_Status | Shape_Length |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | Polyline | 2 | 11 | Working | 2020 | 1223.81 | 36.41 | 1 | 4 | 22 | 13 | 940.530029 | 26.299999 | 1 | 1 | 0.023648 |
| 2 | 2 | Polyline | 1 | 11 | Working | 2013 | 1147.97 | 27.87 | 2 | 4 | 22 | 12 | 1016.549988 | 29.6 | 0 | 1 | 0.030988 |
| 3 | 3 | Polyline | 2 | 11 | Working | 2020 | 1285.47 | 32.87 | 3 | 3 | 22 | 19 | 874.619995 | 39.270001 | 0 | 1 | 0.022081 |
| 4 | 4 | Polyline | 2 | 12 | Working | 2021 | 1695.73 | 34.89 | 4 | 5 | 31 | 18 | 1071.380005 | 31.610001 | 0 | 1 | 0.038754 |
| 5 | 5 | Polyline | 1 | 11 | Working | 2009 | 1438.57 | 24.88 | 5 | 5 | 31 | 20 | 1689.130005 | 37.700001 | 1 | 1 | 0.023945 |
| 6 | 6 | Polyline | 1 | 12 | Working | 2008 | 1336.25 | 35.61 | 6 | 5 | 31 | 2 | 1123.800049 | 41.880001 | 1 | 1 | 0.036099 |
| 7 | 7 | Polyline | 1 | 11 | Faulty | 2012 | 1315.28 | 40.99 | 7 | 4 | 21 | 9 | 1432.959961 | 37.59 | 1 | 0 | 0.019541 |
| 8 | 8 | Polyline | 2 | 11 | Faulty | 2005 | 1519.02 | 31.13 | 8 | 5 | 31 | 5 | 866.73999 | 24.66 | 1 | 1 | 0.031287 |
| 9 | 9 | Polyline | 2 | 11 | Working | 2023 | 1244.8 | 24.86 | 9 | 5 | 31 | 11 | 1329.680054 | 32.279999 | 1 | 1 | 0.039883 |
| 10 | 10 | Polyline | 2 | 11 | Faulty | 2023 | 1252.25 | 34.64 | 10 | 4 | 21 | 14 | 971.450012 | 33.270001 | 0 | 0 | 0.032672 |
| 11 | 11 | Polyline | 2 | 11 | Faulty | 2020 | 1773.92 | 33.57 | 11 | 4 | 22 | 12 | 1478.160034 | 35.599998 | 1 | 0 | 0.03632 |
| 12 | 12 | Polyline | 2 | 12 | Working | 2019 | 828.68 | 30.68 | 12 | 5 | 31 | 5 | 1307.270019 | 24.469999 | 1 | 1 | 0.029772 |
| 13 | 13 | Polyline | 1 | 11 | Working | 2018 | 1362.36 | 29.79 | 13 | 5 | 31 | 9 | 1080.680054 | 32.099998 | 0 | 0 | 0.033821 |
| 14 | 14 | Polyline | 2 | 11 | Faulty | 2007 | 1078.29 | 41.94 | 14 | 4 | 21 | 2 | 1079.040039 | 35.82 | 1 | 0 | 0.020783 |
| 15 | 15 | Polyline | 2 | 12 | Working | 2013 | 830.96 | 30.08 | 15 | 5 | 31 | 6 | 1436.270019 | 25.799999 | 0 | 0 | 0.035417 |

This spatial output allows utility planners to visually inspect high-risk areas and plan targeted field inspections or replacements.

## V. DISCUSSION

This section interprets the results in the context of real-world utility operations, assesses the reliability of the implemented machine learning (ML) models, and discusses the broader implications, limitations, and potential improvements.

### A. *Interpretation of Findings*

The experiment demonstrated the feasibility of using synthetic geospatial utility data combined with environmental parameters to train machine learning models that predict asset failure. Among the models tested, Random Forest consistently outperformed others in terms of classification accuracy (57%) and AUC (0.61), indicating its robustness for tabular, mixed-type data with non-linear patterns.

Key observations include:

*1)* Asset age as a primary contributor confirms that older infrastructure components have a higher likelihood of failure.
*2)* Temperature and rainfall emerged as significant environmental stressors, suggesting that seasonal or regional weather variations should be considered in asset lifecycle management.
*3)* The visual prediction map provided actionable insights for spatially prioritizing maintenance or inspections.

### B. *Practical Implications*

This research has the following real-world implications for electric utility asset management:

*1)* Proactive maintenance planning: By identifying likely-to-fail components ahead of time, utilities can shift from reactive to predictive maintenance, potentially reducing outages and repair costs.
*2)* Risk-aware infrastructure investments: Geospatial prediction maps help target investments in high-risk regions (e.g., coastal or flood-prone zones).
*3)* Digital twin integration: The synthetic GDB structure can serve as a baseline for implementing Geo AI in operational digital twin frameworks used by utilities.

### C. *Model Generalization and Transferability*

Although the models were trained on a synthetic dataset, the structure, domains, and attributes closely mimic real-world utility asset models used in GIS platforms such as ArcGIS Utility Network.

*1)* With access to real sensor data (e.g., SCADA, AMI, IoT weather feeds), this framework can be directly applied and retrained for higher fidelity.
*2)* The use of coded value domains ensures compatibility with existing GIS standards and enterprise utility databases.

### D. *Limitations*

Despite promising results, the study has certain limitations:

*1)* Synthetic data lacks real-world failure patterns, historical outages, or repair logs, which could improve model training significantly.

2) Limited feature diversity: Only a few attributes were used for modeling. Inclusion of additional operational (e.g., load, voltage) and spatial (e.g., proximity to vegetation) variables could enhance accuracy.
3) Small sample size: While 3000 records were sufficient for prototyping, larger datasets would allow for deeper model learning and validation.

### E. Opportunities for Future Work

This foundational study opens several avenues for further exploration:

1) Time series modelling to predict future failures based on trends and deterioration.
2) Integration of satellite imagery (e.g., NDVI, LST) to assess environmental stress more accurately.
3) Deep learning architectures such as Graph Neural Networks (GNNs) for topological feature modeling.
4) Real-time monitoring and alerting via dynamic data feeds and dashboards.

### F. Validation Strategy

To validate this model in production:

1) Field inspection data can be used to confirm the predicted failures.
2) Historical outage datasets can serve as ground truth to retrain or test the models.
3) Cross-validation on different geographic regions (e.g., Odisha vs. Kerala) can help assess geographic generalizability.

### G. Research Question

RQ1: Can machine learning models, when combined with geospatial and environmental data, accurately predict failures in electric utility assets?

As per my study, machine learning models, when integrated with geospatial and environmental data, can provide moderately accurate predictions of electric utility asset failures. In your study, multiple models were evaluated using features derived from a synthetic utility geodatabase enriched with rainfall and temperature attributes. Among the tested models, Random Forest achieved the highest prediction accuracy of 57%, followed by CatBoost, KNN, and Naive Bayes at 53%.

These results demonstrate that

1) There is a discernible pattern between environmental conditions (e.g., rainfall, temperature), asset characteristics (e.g., age, type), and failure likelihood.
2) While the models did not reach high predictive power (due to synthetic data and limited attributes), they show strong potential for operational deployment when trained on real-world datasets.

## VI. CONCLUSION

This research presents a Geo AI based approach for predicting electric utility asset failures by integrating spatial data science, machine learning, and GIS technologies. Focusing on the Indian state of Odisha, we constructed a synthetic utility geodatabase enriched with realistic environmental attributes (rainfall and temperature) and trained multiple machine learning models to assess asset health.

### A. Key Contributions

1) A domain-coded synthetic utility geodatabase (GDB) was created using ArcGIS Pro and ArcPy, emulating a real-world electric distribution network with Electric Line (Polyline), Electric Device (Point), and Electric Junction (Point) feature classes.
2) Environmental stressors such as rainfall and temperature were programmatically integrated into the dataset, allowing for realistic simulation of asset degradation under climatic influence.
3) Machine learning models (Random Forest, CatBoost, KNN, Naive Bayes) were trained using operational and environmental features. Among these, Random Forest showed the best performance with 57% accuracy and the most informative feature importance rankings.
4) A prediction map was generated and visualized in ArcGIS Pro, enabling geospatial interpretation of at-risk assets—a valuable step toward real-world implementation of proactive maintenance planning.

### *B. Insights and Impact*

This work demonstrates the potential of Geo AI to improve decision-making in electric utility operations. By predicting asset failures spatially, utilities can reduce downtime, allocate resources efficiently, and extend the life of critical infrastructure.

While the study used synthetic data due to the lack of openly available electric utility datasets, the methodology is fully transferable to real-world scenarios. It serves as a prototype for integrating ML workflows into geospatial asset management platforms.

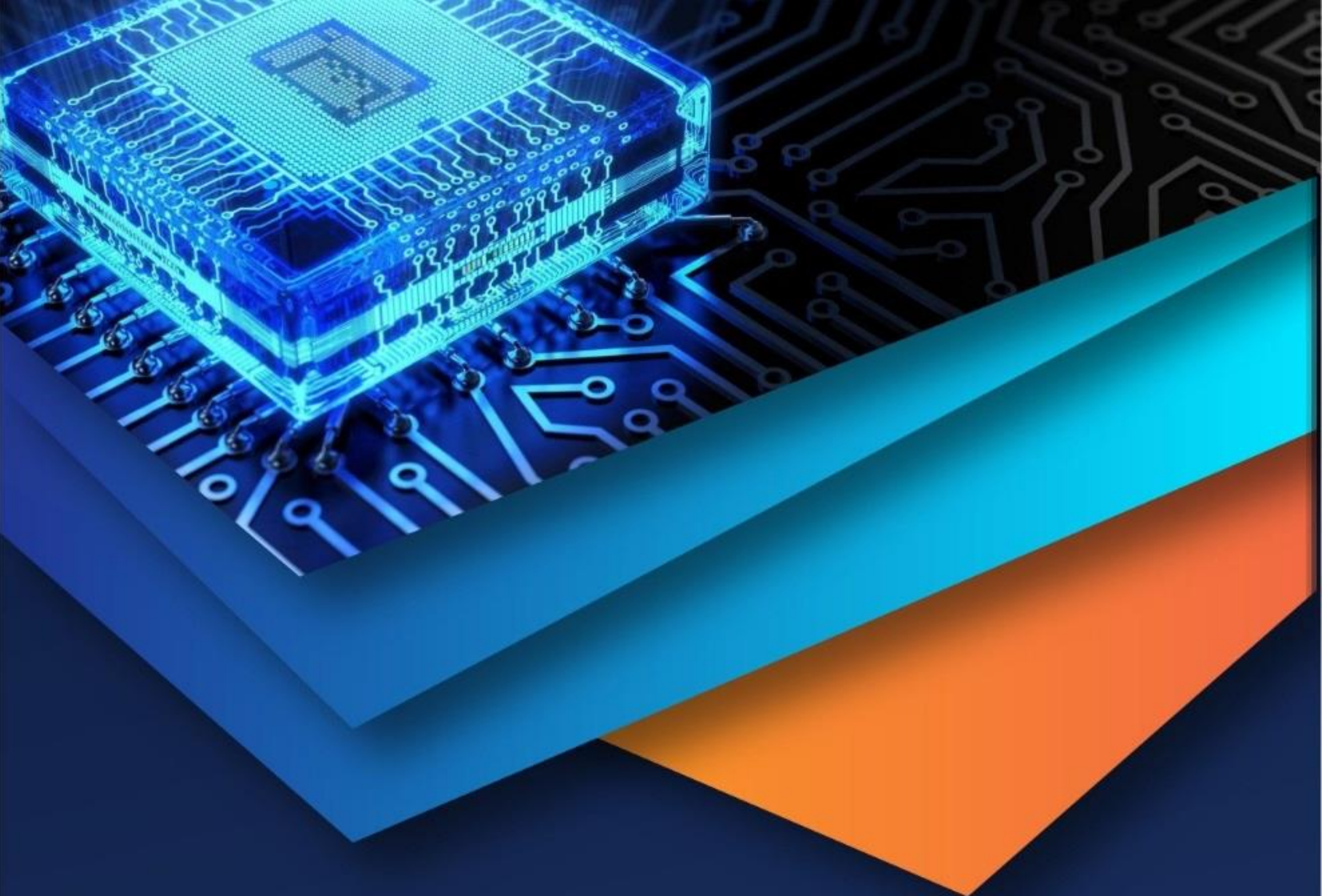
### *C. Future Directions*

Building on this foundation, future work may include:

*1)* Incorporating real asset failure records and outage logs for higher model reliability.
*2)* Integrating remote sensing indices such as NDVI and land surface temperature to improve environmental context.
*3)* Developing automated dashboards or web maps for real-time risk monitoring.
*4)* Exploring deep learning and graph-based models to leverage spatial connectivity in networks.

## REFERENCES

[1] Esri. (2023). ArcGIS Pro SDK Documentation. Retrieved from: https://pro.arcgis.com
[2] Zhou, Y., He, Y., & Zhang, H. (2021). Predictive Maintenance of Utility Assets Using Machine Learning and GIS. IEEE Access, 9, 114203–114215. https://doi.org/10.1109/ACCESS.2021.3105101
[3] Nassiry, D., (2020). Machine Learning in Predictive Maintenance: A Review of the State of the Art. Renewable and Sustainable Energy Reviews, 134, 110404.
[4] Tao, Y., Liu, Y., & Zhang, X. (2020). GeoAI: Spatially Explicit Machine Learning for Environmental Applications. International Journal of Geographical Information Science, 34(3), 385–398.
[5] CHIRPS Dataset. Climate Hazards Group. Retrieved from: https://www.chc.ucsb.edu/data/chirps
[6] MODIS Land Surface Temperature (LST). NASA Earthdata. Retrieved from: https://modis.gsfc.nasa.gov
[7] Pedregosa, F. et al. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825–2830.
[8] Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A.V., & Gulin, A. (2018). CatBoost: Unbiased
[9] https://www.youtube.com/watch%3Fv%3DkRMOKSud9Lk

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