POWER GRID ANOMALY DETECTION AND LOCALIZATION SYSTEM

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PROBLEM STATEMENT

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The traditional methods of fault detection and location are time-consuming and may not provide precise results, leading to prolonged power outages and increase operational costs.

Importance

Accurate fault identification is vital for reducing downtime and operational costs, thereby ensuring the reliability of the electrical distribution network.

Potential Impact

The proposed system aims to significantly reduce power outages, enhance system resilience, and optimize maintenance efforts.

TARGET USERS & MARKET

- **Target Users**

Utilities, electrical distribution companies, and maintenance teams responsible for the operation and maintenance of electrical distribution networks.

- **Total Addressable Market**

All entities managing electrical distribution networks globally.

- **Service Obtainable Market**

Companies with the resources to implement and benefit from the proposed fault prediction system.

PROPOSED SOLUTION

Key Features

- Machine learning model for fault prediction.
- Geospatial visualization of fault locations on a world map for better insights.
- Feature engineering to enhance model accuracy and interpretability.

Technical Architecture

- Data generation to create synthetic data for training and testing.
- Random Forest Classifier for fault prediction.
- Geospatial analysis using GeoPandas and Matplotlib

I present a solution utilizing machine learning and geospatial analysis to predict and locate faults in the underground and overhead line distribution network.

CODE RUNTHROUGH

Data Generation

- A function generate_coordinates generates random coordinates within the continent.
- Random data is generated with features such as current, voltage, direction, fault_history, latitude, longitude, and weather.

Data Preprocess

- The generated data is loaded into a Pandas DataFrame (df).
- Missing data is handled by filling NaN values with zeros.
- Categorical features (direction and weather) are one-hot encoded for the machine learning model.
- Numerical features (current, voltage, latitude, longitude) are normalized using StandardScaler.
- The latitude and longitude are converted into a GeoDataFrame for geospatial analysis.

Model Training

- The target variable (fault_history) is the variable to be predicted.
- Features (current, voltage, latitude, longitude, direction, weather) are used to make predictions.
- The dataset is split into training and testing sets (80% training, 20% testing) using train_test_split from sklearn.model_selection.
- A Random Forest Classifier is initialized with a random seed for reproducibility.
- The model is trained on the training dataset using model.fit(X_train, y_train).

Model Evaluation

- The trained model is used to predict the fault_history on the test dataset.
- The accuracy of the model is calculated using accuracy_score from sklearn.metrics.
- The importance of each feature in making predictions is determined using model.feature_importances_.

Model Persistence

The trained model is saved using joblib for future use or deployment.

GIS Integration

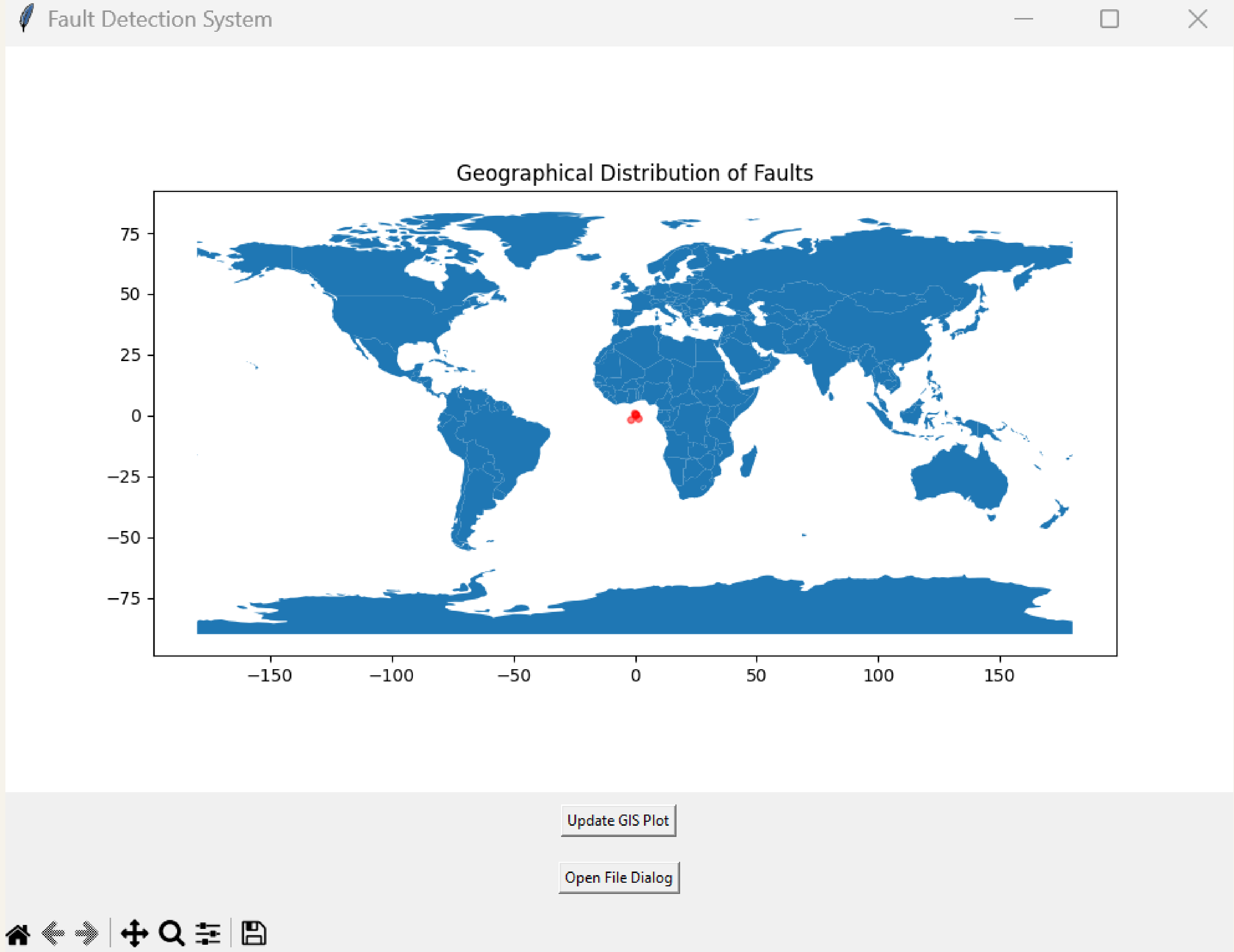
The geographical distribution of faults is visualized using GeoPandas and Matplotlib. The map includes markers for fault locations.

User Interaction

A Tkinter GUI is created to interact with the GIS plot, allowing users to update the plot and open a file dialog to load different datasets.

OUTPUT

```
*IDLE Shell 3.11.3*
File  Edit  Shell  Debug  Options  Window  Help
Python 3.11.3 (tags/v3.11.3:f3909b8, Apr  4 202
AMD64)] on win32
Type "help", "copyright", "credits" or "license
>>>
= RESTART: C:/Users/urmim_fax022t/AppData/Local
t.py
Accuracy: 1.0
Feature Importance:
current: 0.14492753623188406
voltage: 0.32367149758454106
latitude: 0.21739130434782608
longitude: 0.10628019323671498
direction_North: 0.0
direction_West: 0.0
weather_Cloudy: 0.11111111111111112
weather_Rainy: 0.019323671497584544
weather_Sunny: 0.07729468599033816
```



FUTURE WORK

Potential Features

- Integration with real-time data sources for continuous monitoring.
- Advanced anomaly detection techniques for fault identification.
- Collaboration with GIS systems for more comprehensive geographical analysis.

Plans for scaling

- Integration with larger datasets for improved model generalization.
- Collaboration with industry partners for real-world implementation and validation.
- Continuous refinement based on user feedback and evolving technologies.

CONCLUSION

The proposed fault prediction and location system aim to revolutionize the electrical distribution network's maintenance approach. By combining machine learning and geospatial analysis, the system provides a holistic solution for quick and accurate fault identification, contributing to improved system reliability and reduced operational costs. Continuous refinement and scalability are integral parts of the project's roadmap, ensuring its effectiveness in real-world scenarios.

THANK YOU