EV CHARGING STATION OPTIMIZATION SYSTEM

https://ev-charginging-recommendation-mabfw5ngasqzftrv2adent.streamlit.app/

Data-Driven Approach to Smart Mobility

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WHAT IS THE PROJECT ABOUT??

To design a data-driven optimization model that analyzes multiple factors such as traffic density, population clusters, grid availability, and existing chargers to recommend optimal locations for new EV stations, ensuring maximum utilization and minimal costs.

Lower operating and maintenance costs over the vehicle's lifetime.
Many governments offer incentives, subsidies, and policies promoting EV adoption.
Continuous improvements in battery technology and charging speed make EVs more practical.
Key to building smart, green cities with reduced dependence on fossil fuels.

ELECTRIC VEHICLE

CHALLENGES:

High upfront investment costs.

Uneven distribution of EV

Power grid limitations.

Dynamic changes in traffic and vehicle density over time.

Need for accessible, efficient, and reliable EV charging infrastructure.

Inconvenience for longer trips causing reduced EV adoption.

KEY FACTORS FOR OPTIMAL PLACEMENT

Population Density: More people = more potential users.

Traffic Patterns: High traffic areas need more stations.

Existing Charging Stations: Avoid redundancy.

Power Availability: Ensure stable electricity supply.

Proximity to Highways, Workplaces, and Malls.

PROJECT APPROACH

Step 1: Data Collection :

Gathered datasets: Kaggle, Government open dataset, Geo-spatial station coordinates

Features used:

Latitude, Longitude, Vehicle Type (encoded , Charging Duration (in seconds), Availability (target)

Step 2: Data Preprocessing and Cleaning

Handled missing values, removed outliers, normalized datasets using Standard Scaler and MinMaxScaler.

Encoded categorical variables (vehicle types, area categories).

Step 3: Exploratory Data Analysis (EDA)

Performed heatmaps, scatter plots, and correlation matrices to uncover relationships.

Found strong correlation between traffic flow and potential EV charging demand.

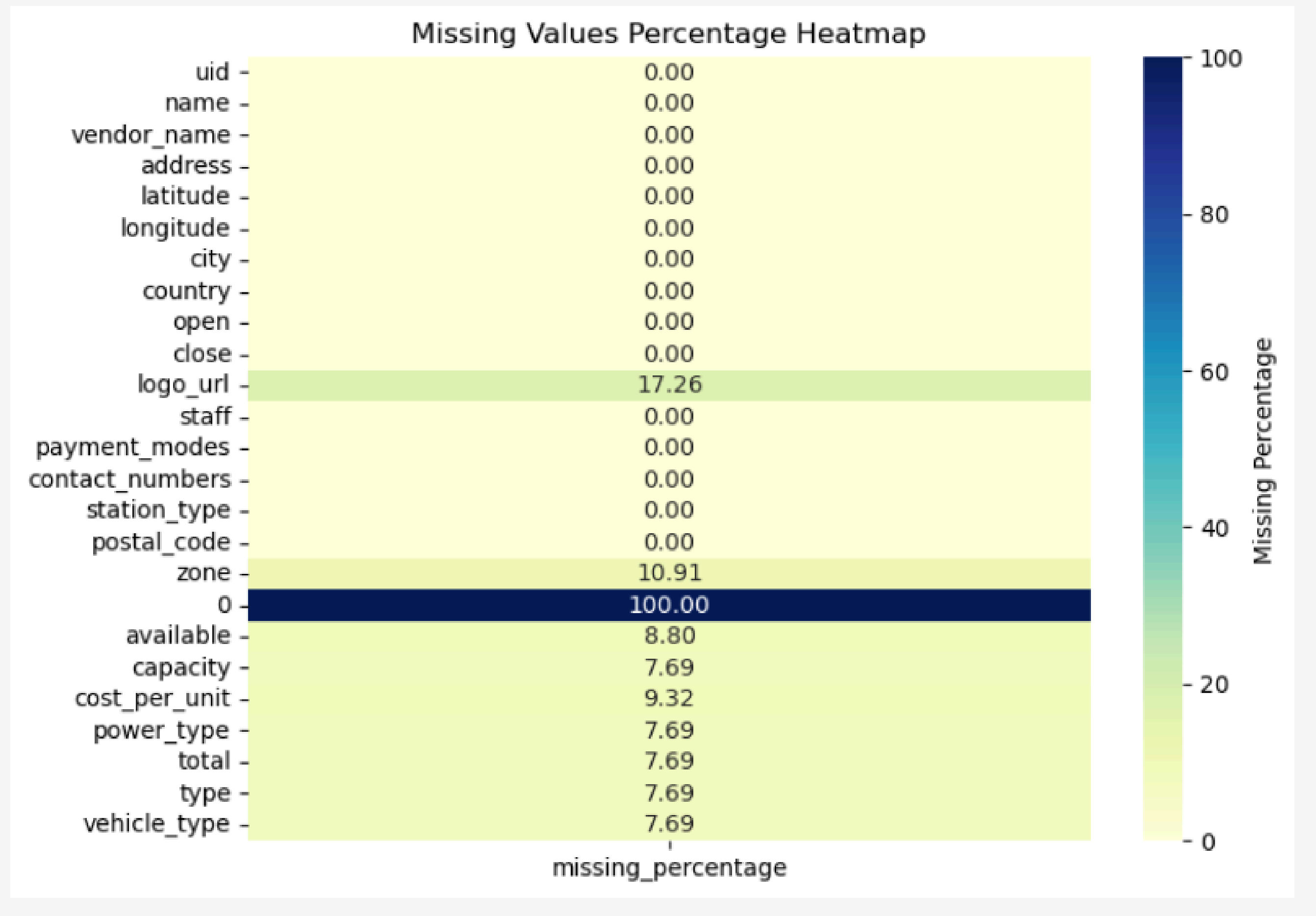
Step 4: Feature Engineering

Derived additional features like "distance from nearest station" and "charging demand score".

DATA COLLECTION

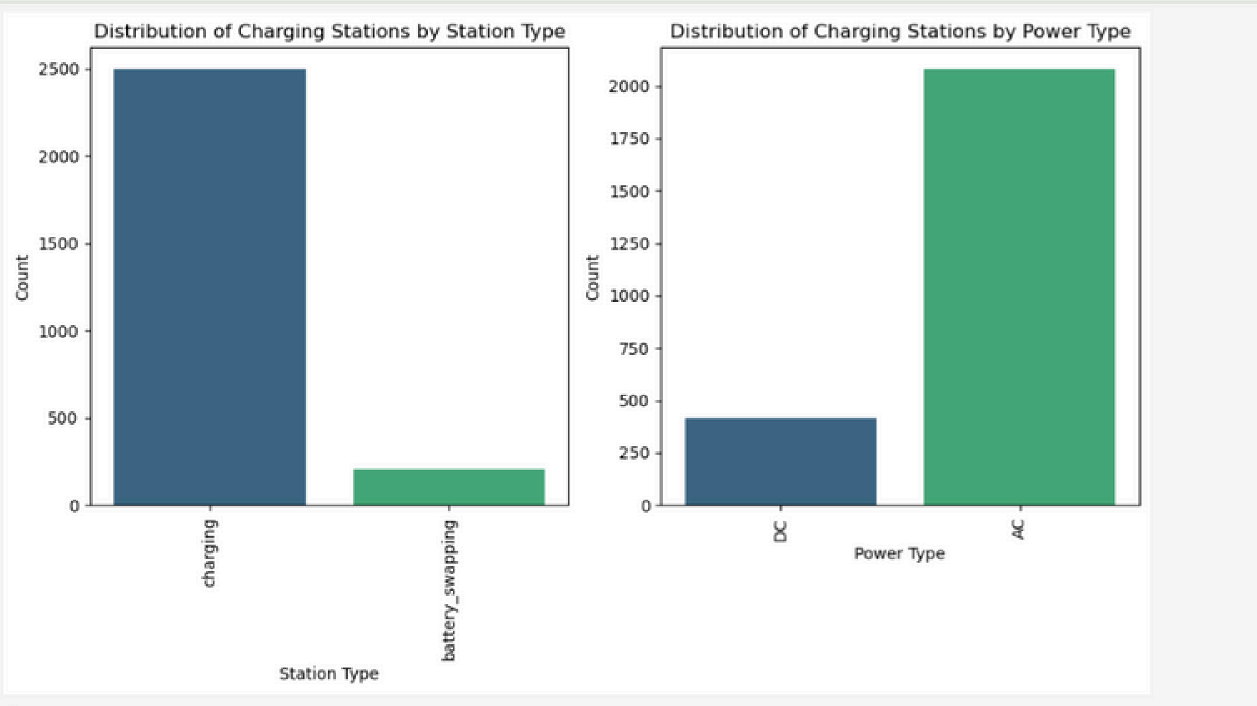
```
Index([            'uid',            'name',      'vendor_name',
               'address',        'latitude',        'longitude',
                  'city',         'country',             'open',
                 'close',        'logo_url',            'staff',
         'payment_modes', 'contact_numbers',     'station_type',
           'postal_code',            'zone',                  0,
             'available',        'capacity',    'cost_per_unit',
            'power_type',           'total',             'type',
          'vehicle_type'],
      dtype='object')
```

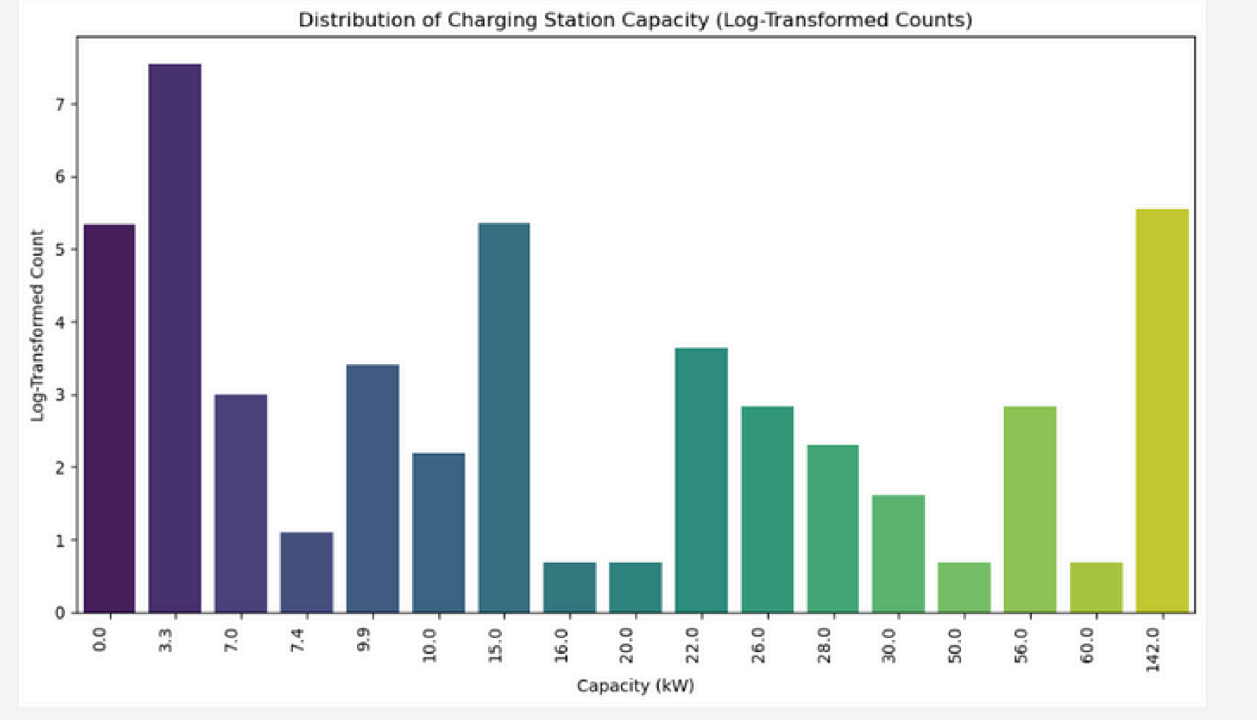
	uid	name	vendor_name	address	latitude	longitude	city	country	open	close	...	postal_code	zone	0	available	capacity	cost_per_unit
0	STATIC12	GensolCharge Pvt. Ltd.	GensolCharge Pvt. Ltd.	NDSE Grid, BRPL South Extension	28.568238	77.219666	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	NaN
1	STATIC14	REIL	REIL	Scada office kalka ji	28.541995	77.260583	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	3.3 kW	NaN
2	STATIC15	REIL	REIL	Ashram Chowk Mathura Road	28.571189	77.259806	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	NaN
3	STATIC16	REIL	REIL	Nizamuddin Railway station	28.588991	77.253240	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	NaN
4	STATIC17	BluSmart	BluSmart	BSES Bhawan, Nehru Place, New Delhi	28.549427	77.254636	Delhi	India	00:00:00	23:59:59	...	110001	central-delhi	NaN	NaN	15 kW	NaN

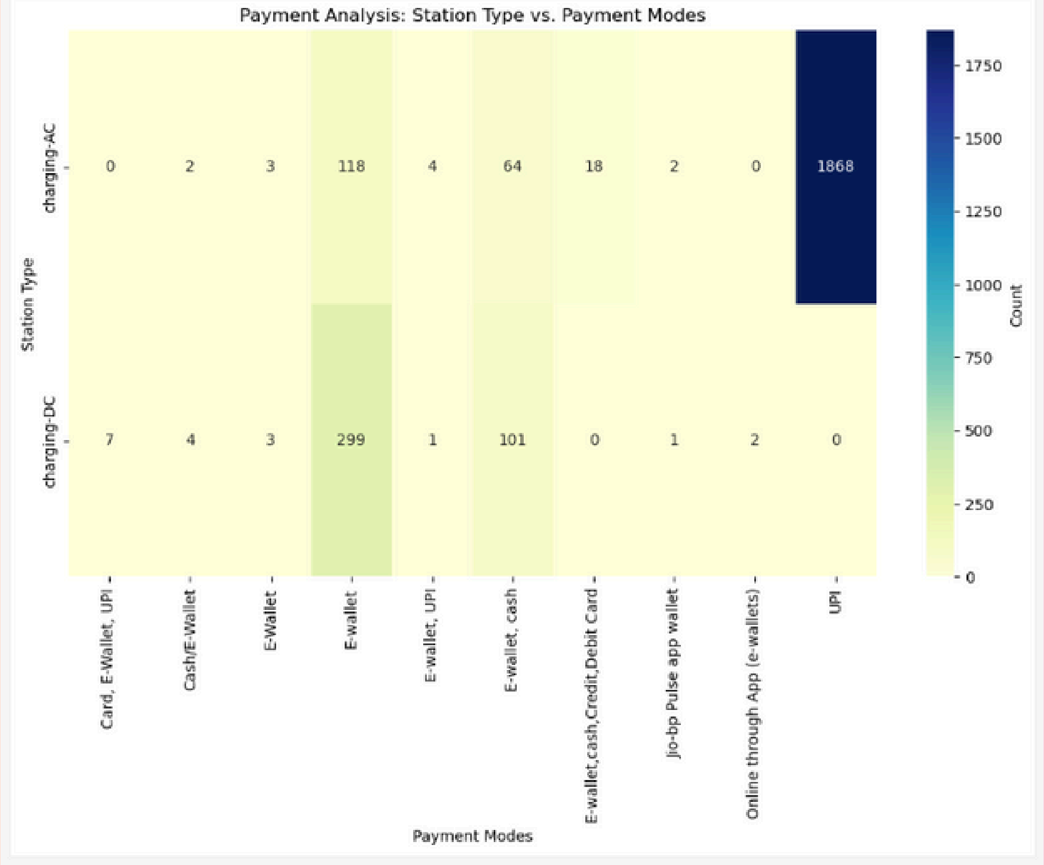


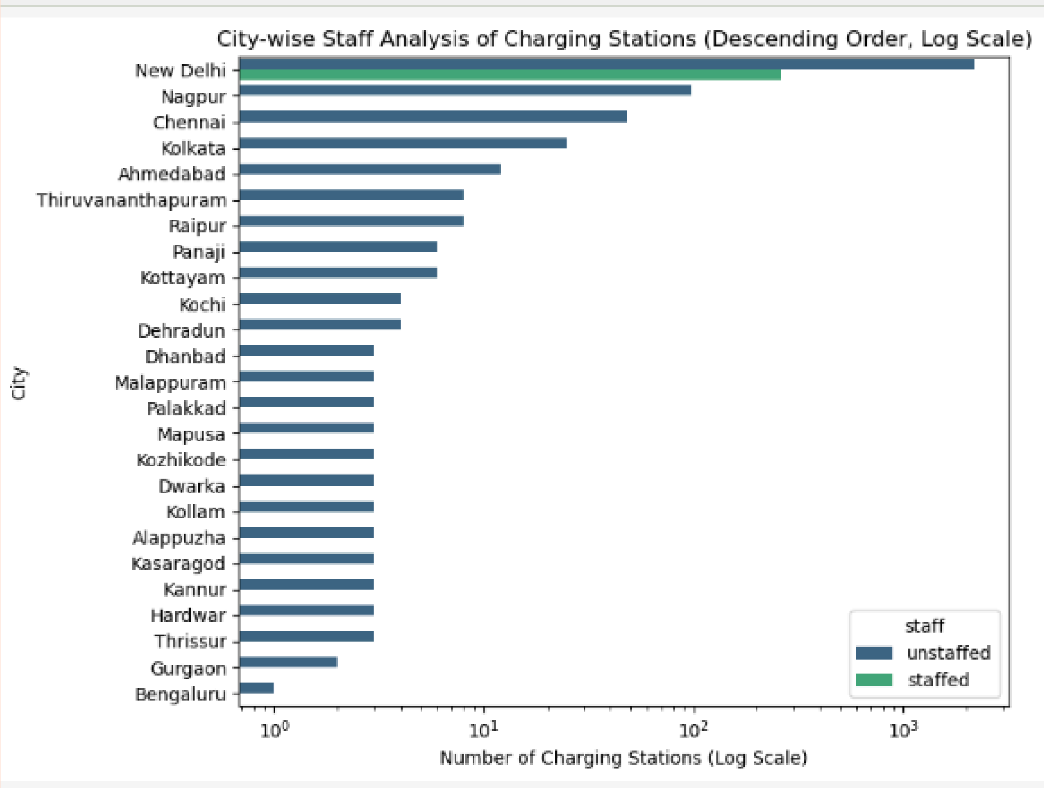
	latitude	longitude	open	close	payment_modes	station_type	0	available	capacity	cost_per_unit	power_type	total	type	vehicle_type	duration
0	28.568238	77.219666	2025-04-27 00:00:00	2025-04-27 23:59:59	Card, E-Wallet, UPI	1	NaN	NaN	15.0	NaN	1	2.0	4	2	0 days 23:59:59
1	28.541995	77.260583	2025-04-27 00:00:00	2025-04-27 23:59:59	E-Wallet	1	NaN	NaN	3.3	NaN	0	3.0	3	0	0 days 23:59:59
2	28.571189	77.259806	2025-04-27 00:00:00	2025-04-27 23:59:59	E-Wallet	1	NaN	NaN	15.0	NaN	1	2.0	4	2	0 days 23:59:59
3	28.588991	77.253240	2025-04-27 00:00:00	2025-04-27 23:59:59	Cash/E-Wallet	1	NaN	NaN	15.0	NaN	1	4.0	4	2	0 days 23:59:59
4	28.549427	77.254636	2025-04-27 00:00:00	2025-04-27 23:59:59	Cash/E-Wallet	1	NaN	NaN	15.0	NaN	1	1.0	4	2	0 days 23:59:59
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2700	13.078481	80.249480	2025-04-27 00:00:00	2025-04-27 23:59:00	E-wallet	1	NaN	0.0	15.0	₹12.93 per unit	1	1.0	14	2	0 days 23:59:00
2701	13.078481	80.249480	2025-04-27 00:00:00	2025-04-27 23:59:00	E-wallet	1	NaN	0.0	142.0	₹20.14 per unit	1	2.0	7	2	0 days 23:59:00
2702	13.078481	80.249480	2025-04-27 00:00:00	2025-04-27 23:59:00	E-wallet	1	NaN	0.0	142.0	₹20.14 per unit	1	2.0	12	2	0 days 23:59:00

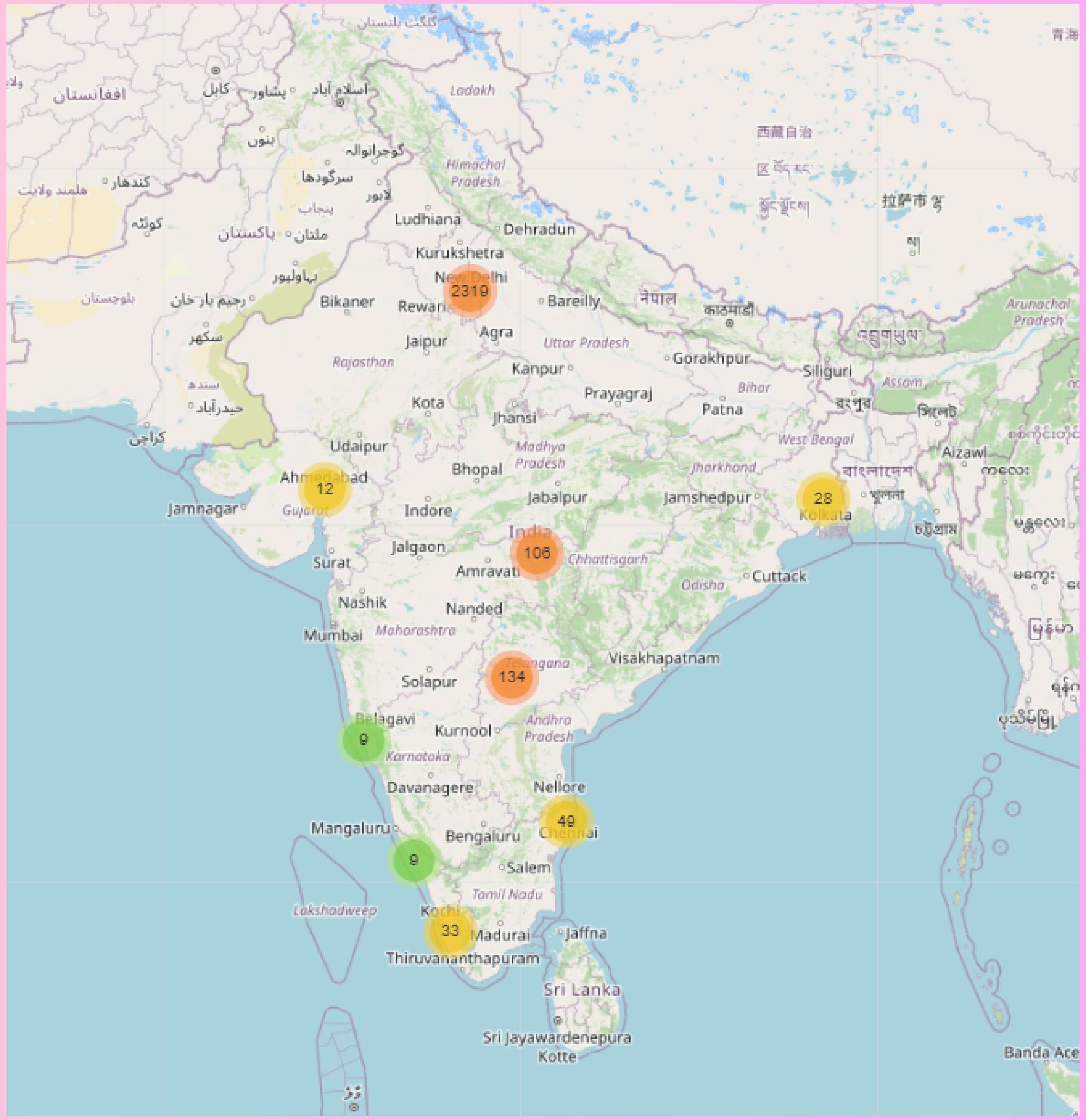
EDA - OBSERVATIONS











MODELS USED

- K-Nearest Neighbors (KNN): Classifies a data point based on how its neighbors are classified.
- Logistic Regression: Estimates the probability of a binary outcome using a logistic function.
- Decision Tree Classifier: Splits data into branches based on feature values to make decisions.
- Random Forest Classifier: Uses an ensemble of decision trees to improve accuracy and reduce overfitting.
- Support Vector Machine (SVM): Finds the optimal hyperplane that separates data into classes with the maximum margin.
- XGBoost: A powerful gradient boosting algorithm that builds trees sequentially with optimized performance.
- Adaboost: Combines multiple weak learners by focusing on errors made by previous models to improve accuracy.
- Gradient Boosting: Builds an additive model in a forward stage-wise fashion by optimizing a loss function.

PERFORMANCE METRICS USED

- Accuracy
- R^2 Score (Coefficient of Determination)
- Root Mean Square Error (RMSE)
- Cross-Validation Score

Among the various models tested—including Logistic Regression, Decision Trees, Random Forest, SVM, and Gradient Boosting methods—K-Nearest Neighbors (KNN) emerged as the best performer in terms of balancing accuracy, generalization ability, and interpretability.

APPLICATION ARCHITECTURE

Frontend: Streamlit Web App

Backend:

KNN Model Predictions

Data Processing with Pandas

Visualization:

Interactive Map with Pydeck

Deployment:

Streamlit Local Server + Cloud Hosting

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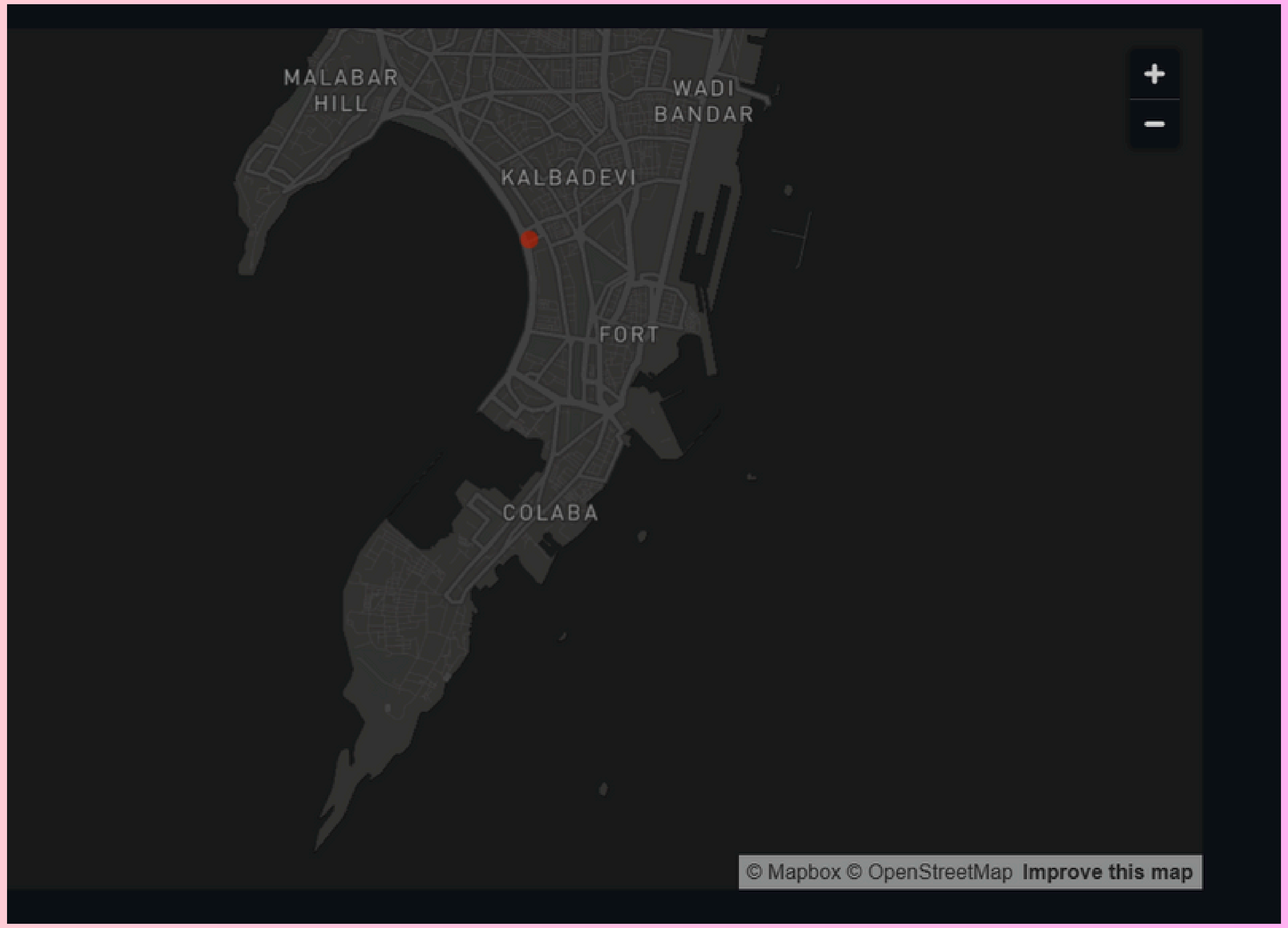

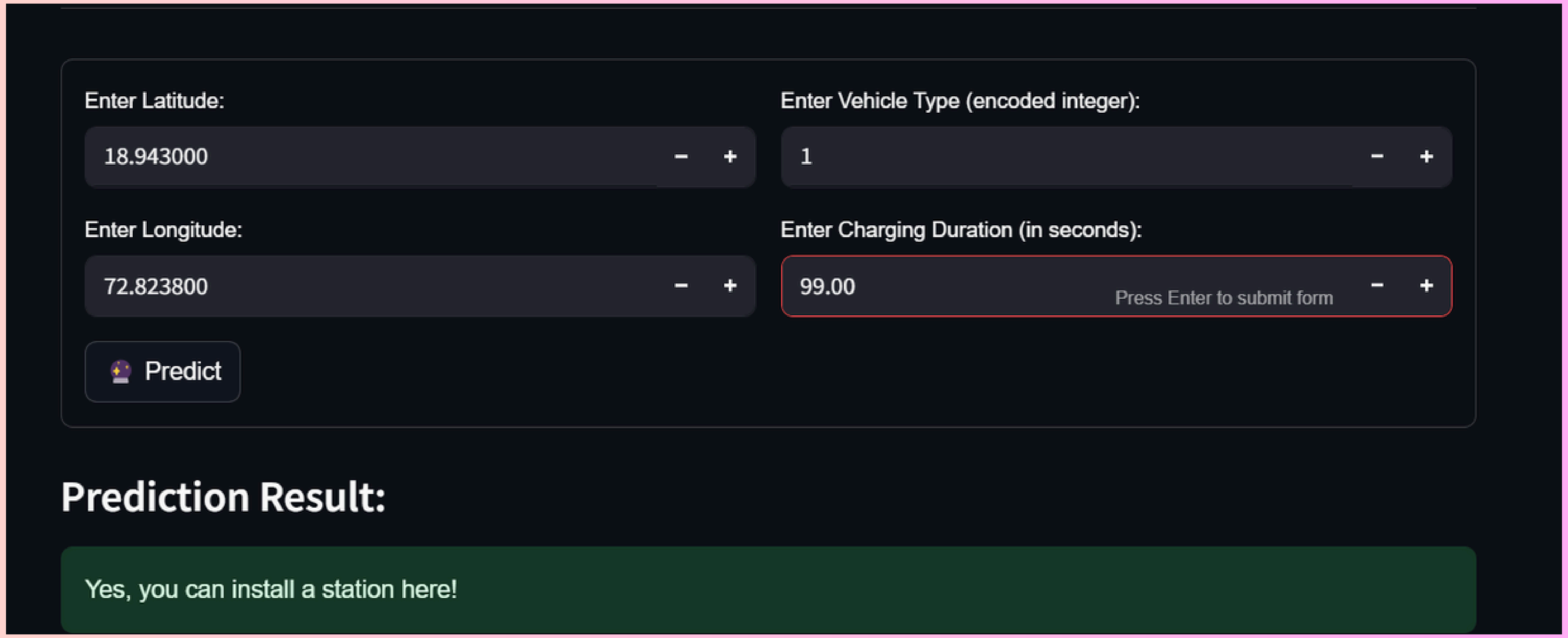

OBSERVATIONS

Population Density and Traffic Flow were found to be the strongest predictors for charger demand.

Certain suburban areas with heavy traffic lacked proper charging facilities, creating hidden demand pockets.

Power Infrastructure sometimes limited the installation even if the location had high user demand.

The KNN model successfully captured the irregular distribution of traffic corridors, outperforming linear and tree-based models in flexibility and spatial accuracy.

FUTURE SCOPE OF THE PROJECT

Short-term Enhancements:

Incorporate real-time traffic data from Google Maps API.

Improve model with XGBoost for even better predictive capabilities.

Long-term Vision:

Develop a mobile app version for EV users to locate nearby stations.

Improve Accuracy for large datasets.

Dynamic re-optimization based on changing urban mobility patterns and EV adoption rates.

THANK YOU