

Data Driven Analysis of EV Charging Infrastructure - Medium/Heavy duty Vehicles



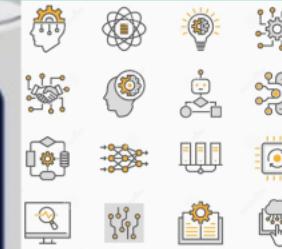
Data Engineering



Machine Learning Models



Machine Learning Models and Comparisons



**Group 6
Under the Guidance of Dr. Zeyu Jerry Gao**

**Lohitha Vanteru
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Pranavi Sandrugu
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Web system design and development



System Implementation

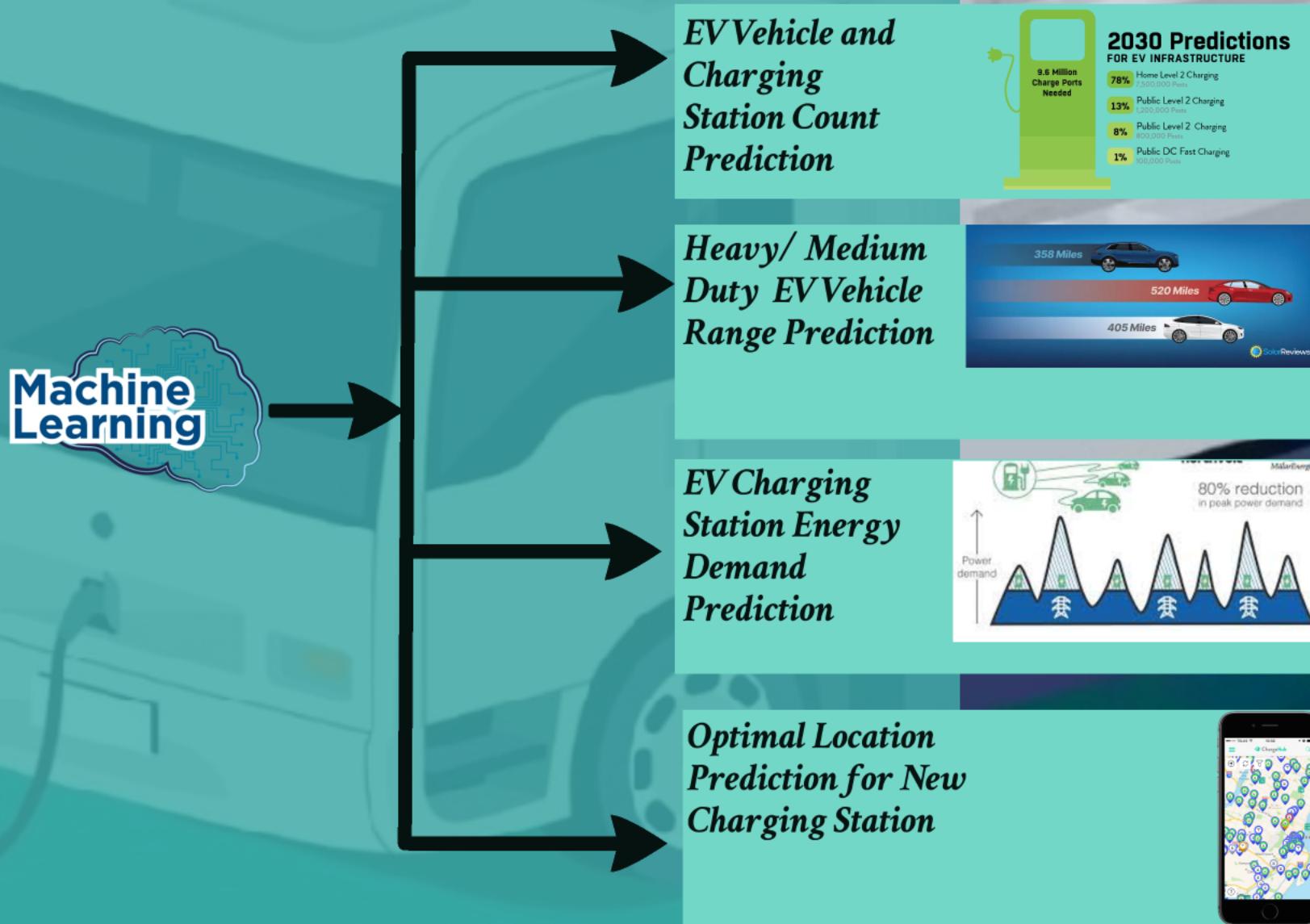


Training and Test Data Sets

Dataset/Task	Raw	Preprocessed	Prepared			
			Total Rows	Train Rows	Test Rows	Validation Rows
CA Vehicle Registration Data	35,742	35713	35713	28571	3571	3571
CA EV Charging Station Data	14862	14835	14835	11869	1483	1483
Vehicle Fleet Transactions Data	4,28,963	4,28,609	4,28,609	3,42,887	42861	42861

All the Datasets are split into 80:10:10 ratio

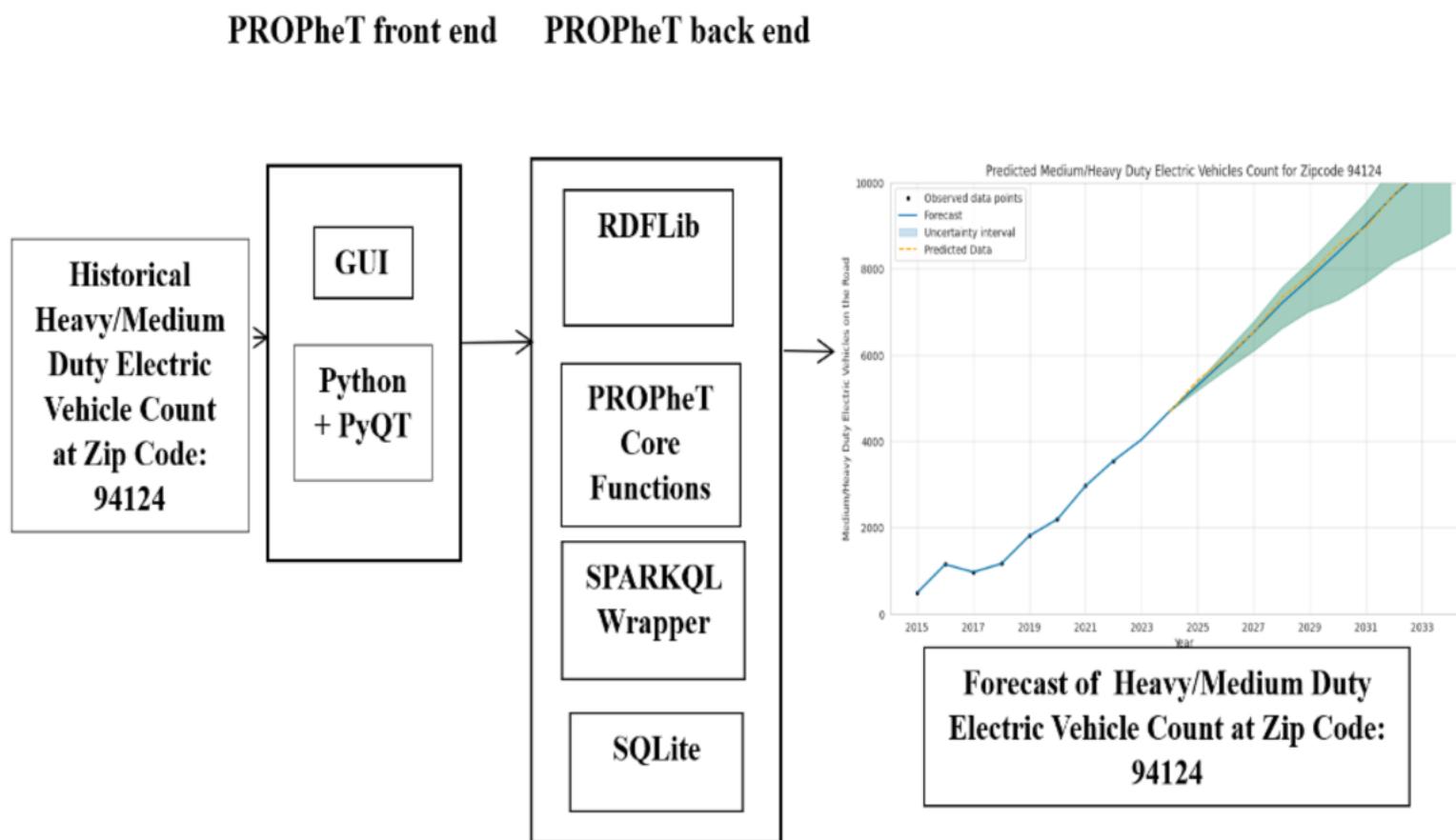
Proposed Machine Learning Models



FORECASTING HEAVY DUTY AND MEDIUM DUTY EV COUNT CHARGING STATIONS

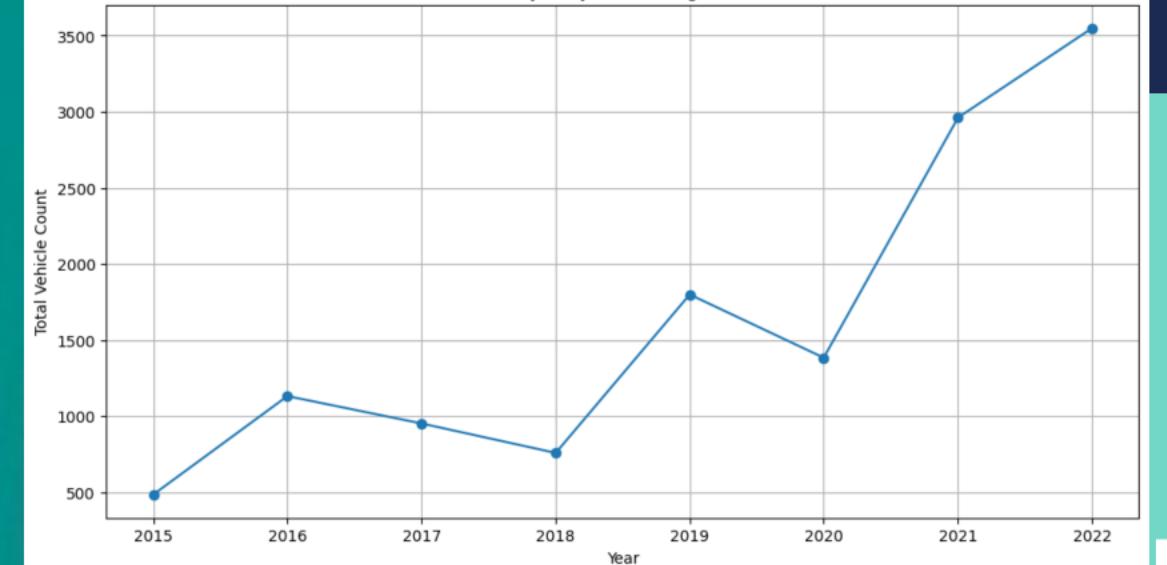
PROPHET Model Architecture: Improvements

To Predict and forecast the future count of Heavy Duty and Medium Duty Vehicles and the required EV charging stations to cater the demand.



- 1 Fine-tuned through hyperparameter optimization.
- 2 Adjusting critical parameters like `changepoint_prior_scale` and `seasonality_prior_scale`
- 3 Integrated additional regressors, consequently improving its predictive accuracy.

Historical Count of Heavy Duty Vehicle registration - CA (2015-2022)



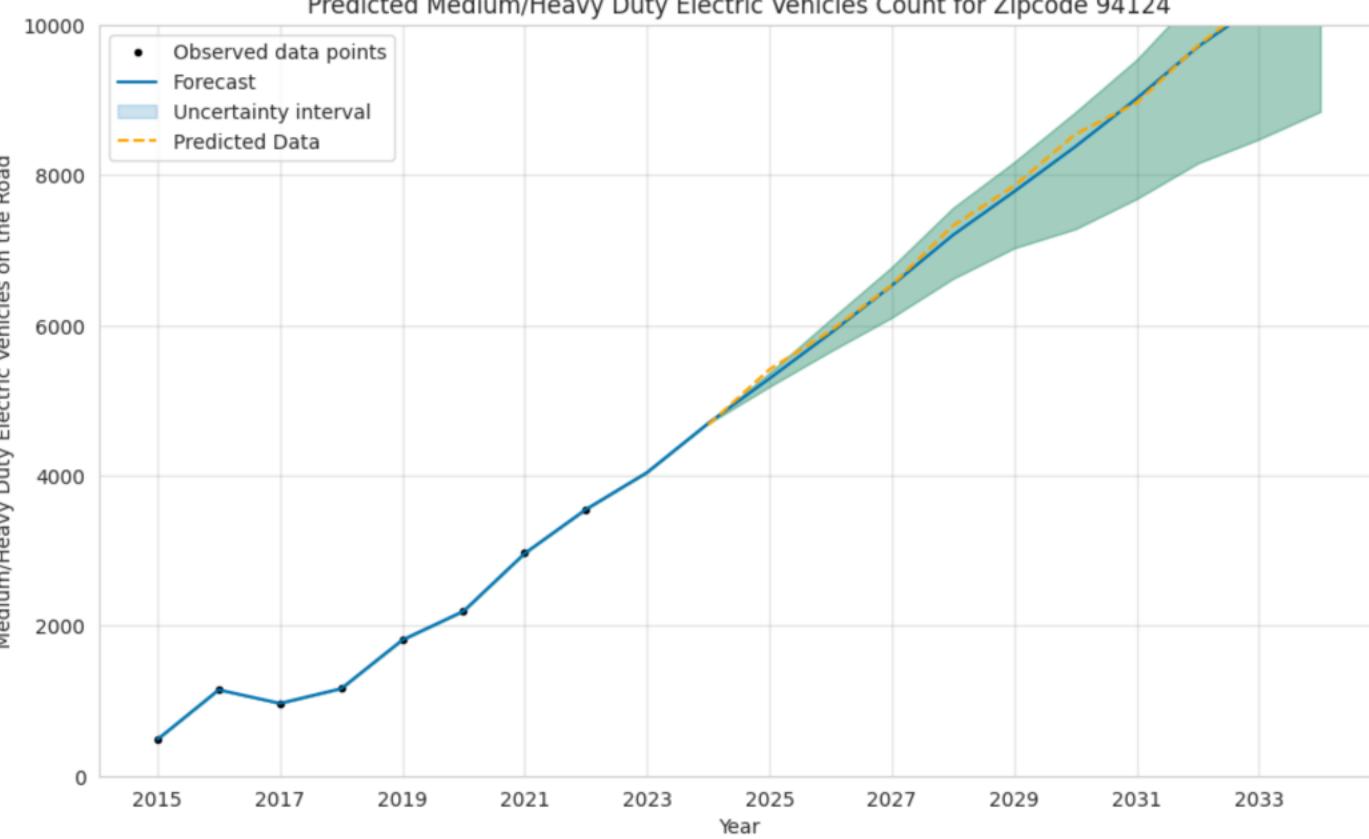
Historical Vehicle Count



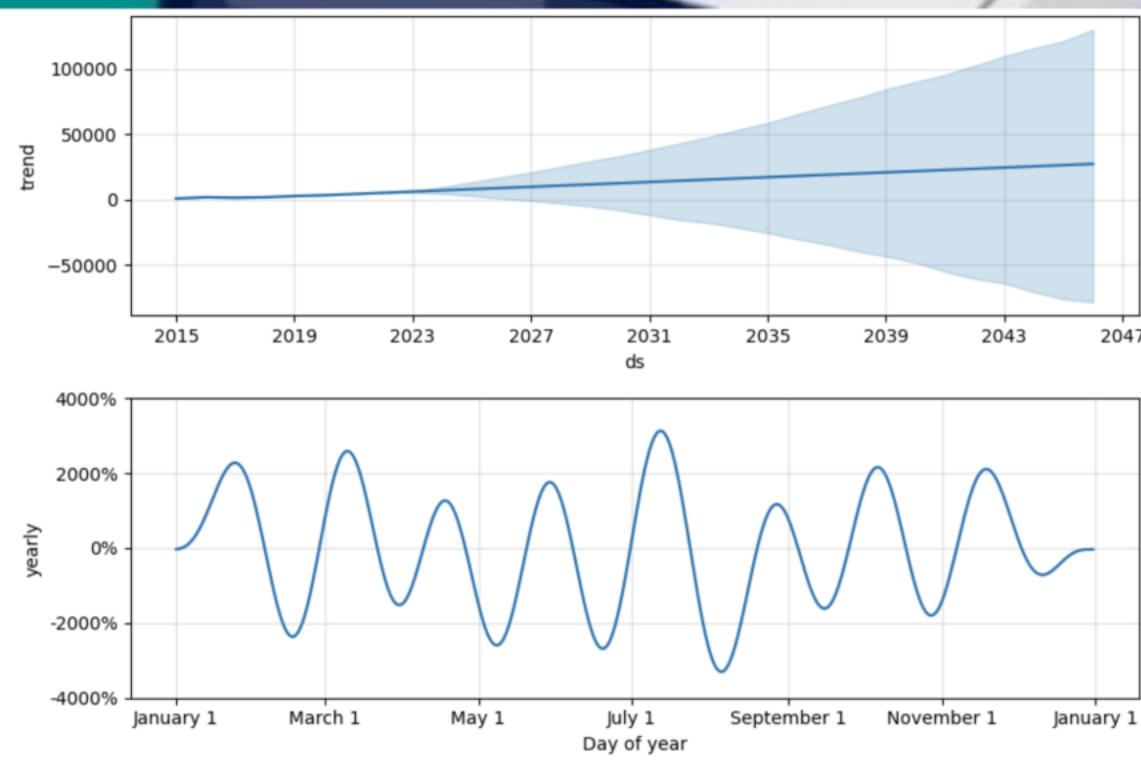
*Forecasting Results
for each Zip Code*



Predicted Medium/Heavy Duty Electric Vehicles Count for Zipcode 94124

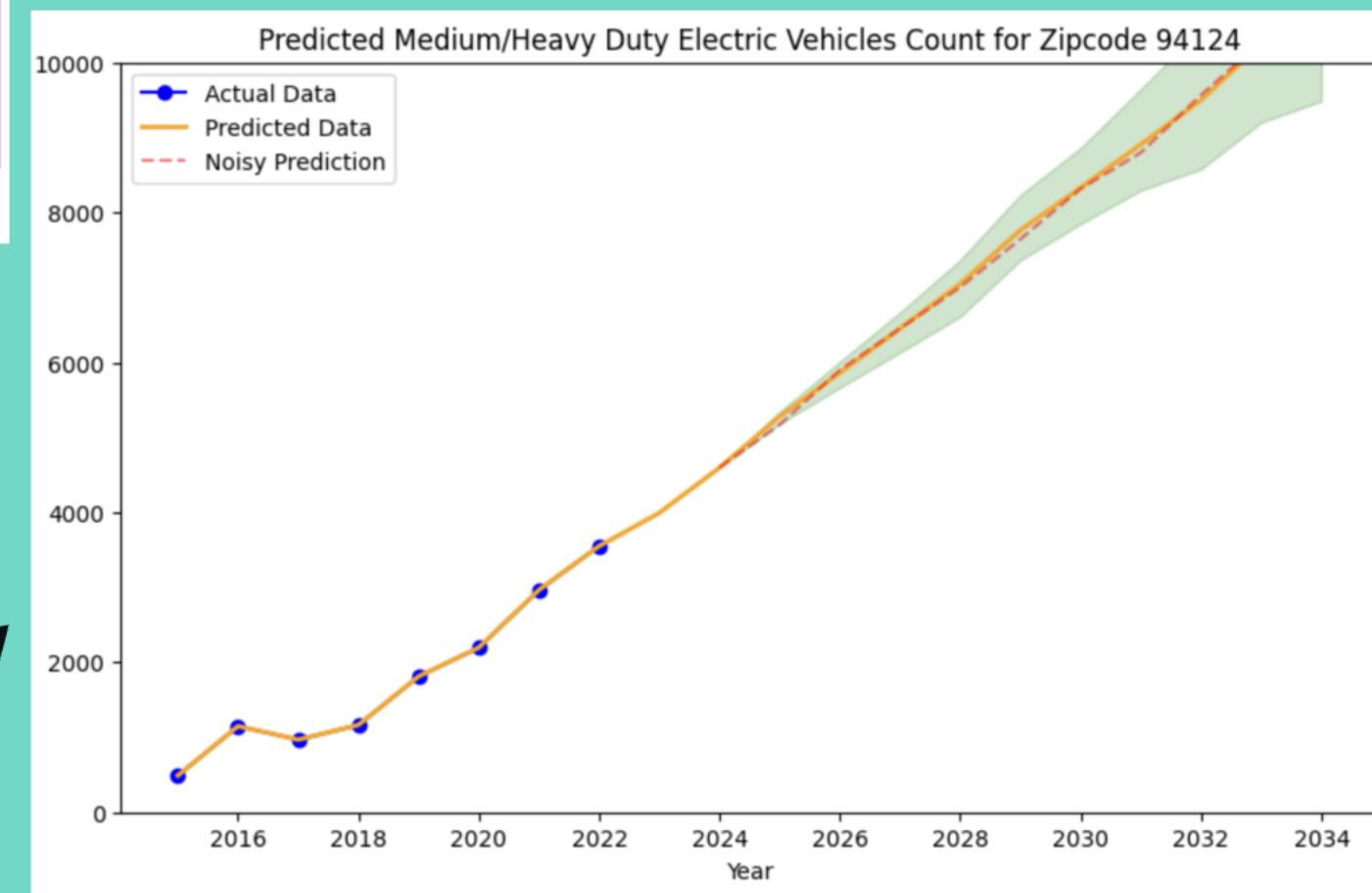


Improved



Forecasting Results for each Zip Code

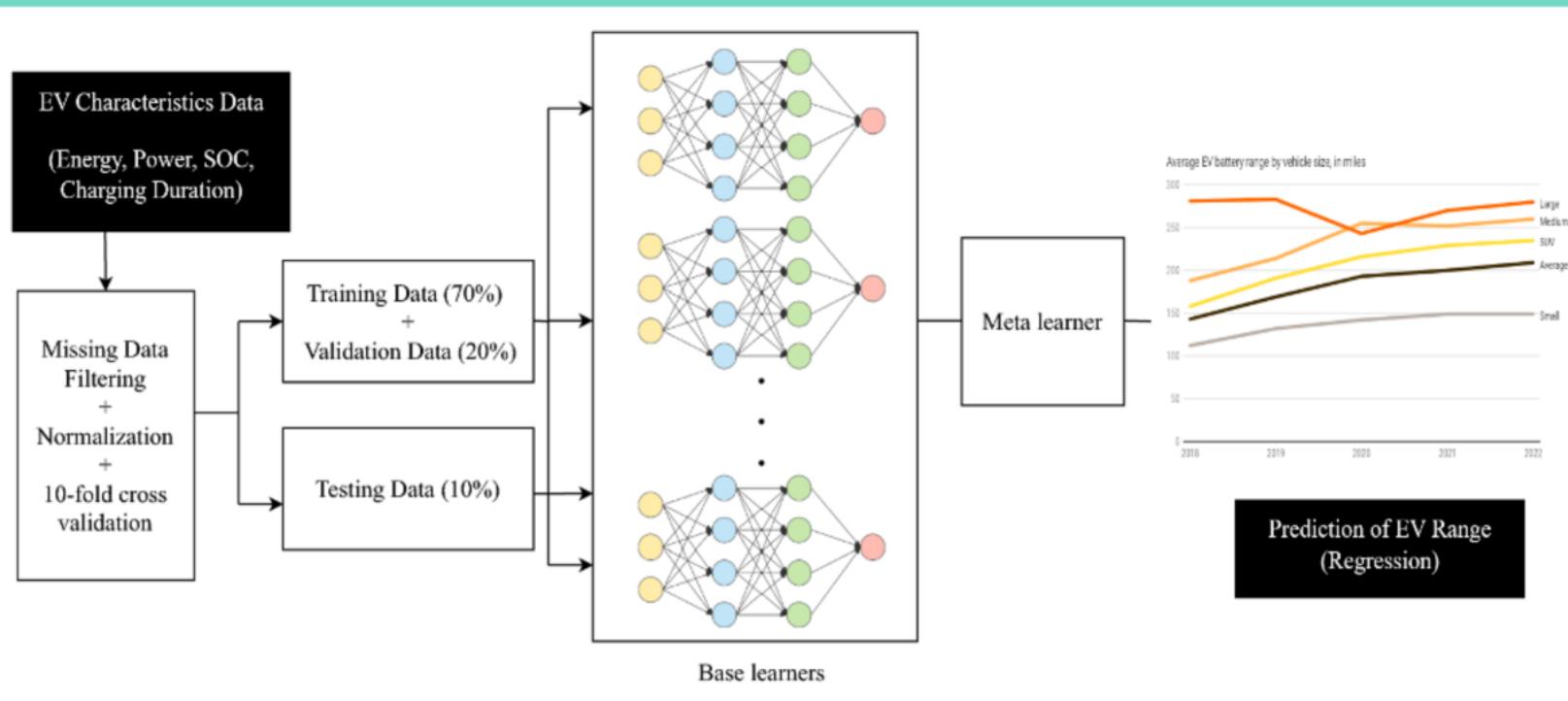
Yearly Trend



PREDICTING VEHICLE RANGE OF HEAVY DUTY AND MEDIUM DUTY EV

Stacking Regressor Model Architecture- Weighted Fusion Voting : Improvements

To forecast range of heavy and medium duty vehicles of each weight class using the characteristics like charging duration, state of charge to the battery.



Incorporated L1 regularization (Lasso) with a regularization strength (alpha) of 0.005 to mitigate overfitting

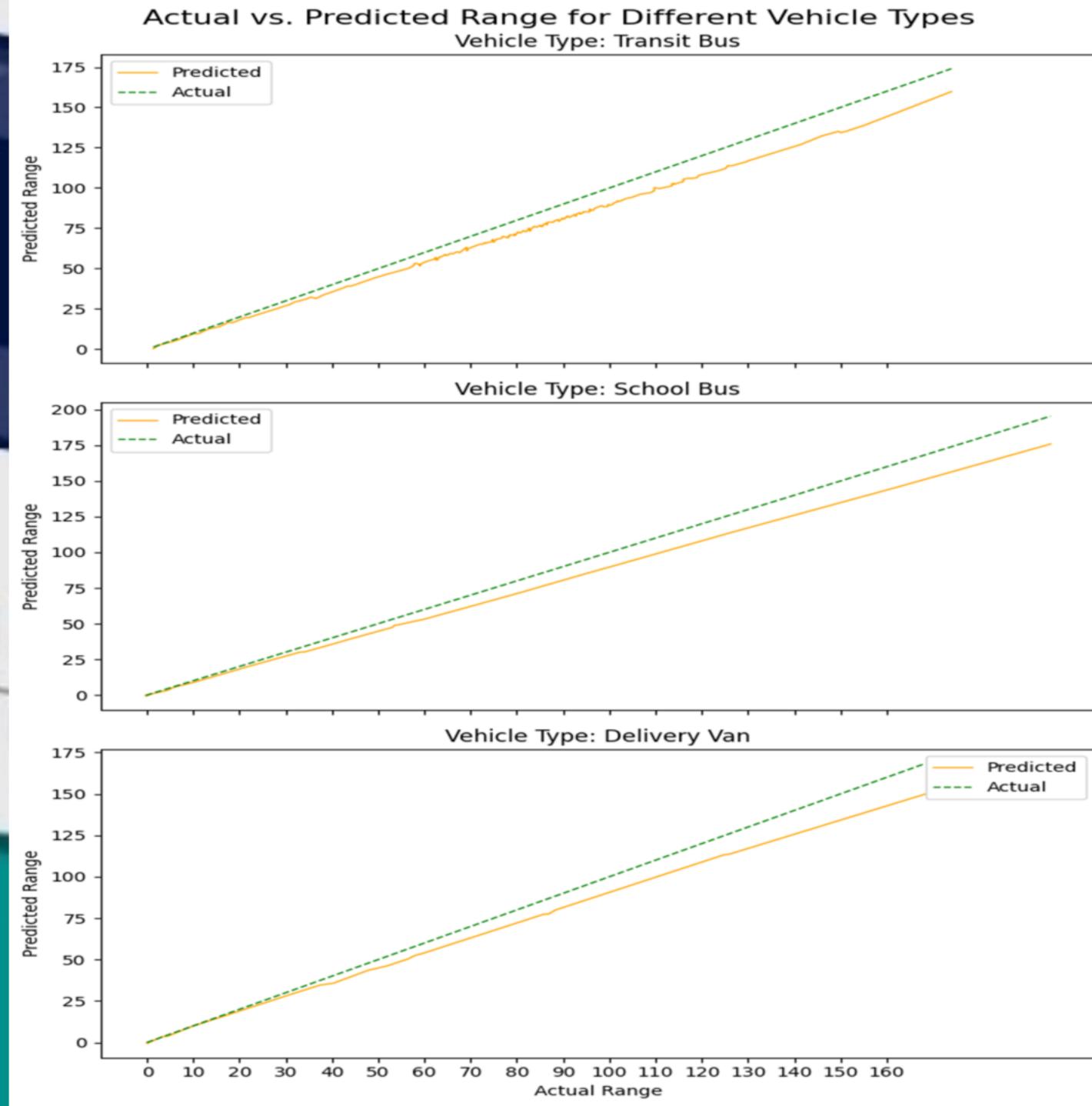
1 Applied Min-Max scaling to ensure consistent impact of each feature on the model

2 Utilized a Gradient Boosting regressor with 100 estimators for improved ensemble learning

3 Incorporated L1 regularization with strength (alpha) of 0.005 to mitigate overfitting

4 Utilized two hidden layers (100 nodes each) and a Rectified Linear Unit (ReLU) activation function in MLP to explicitly capture complex non-linear dependencies in charging duration, state of charge

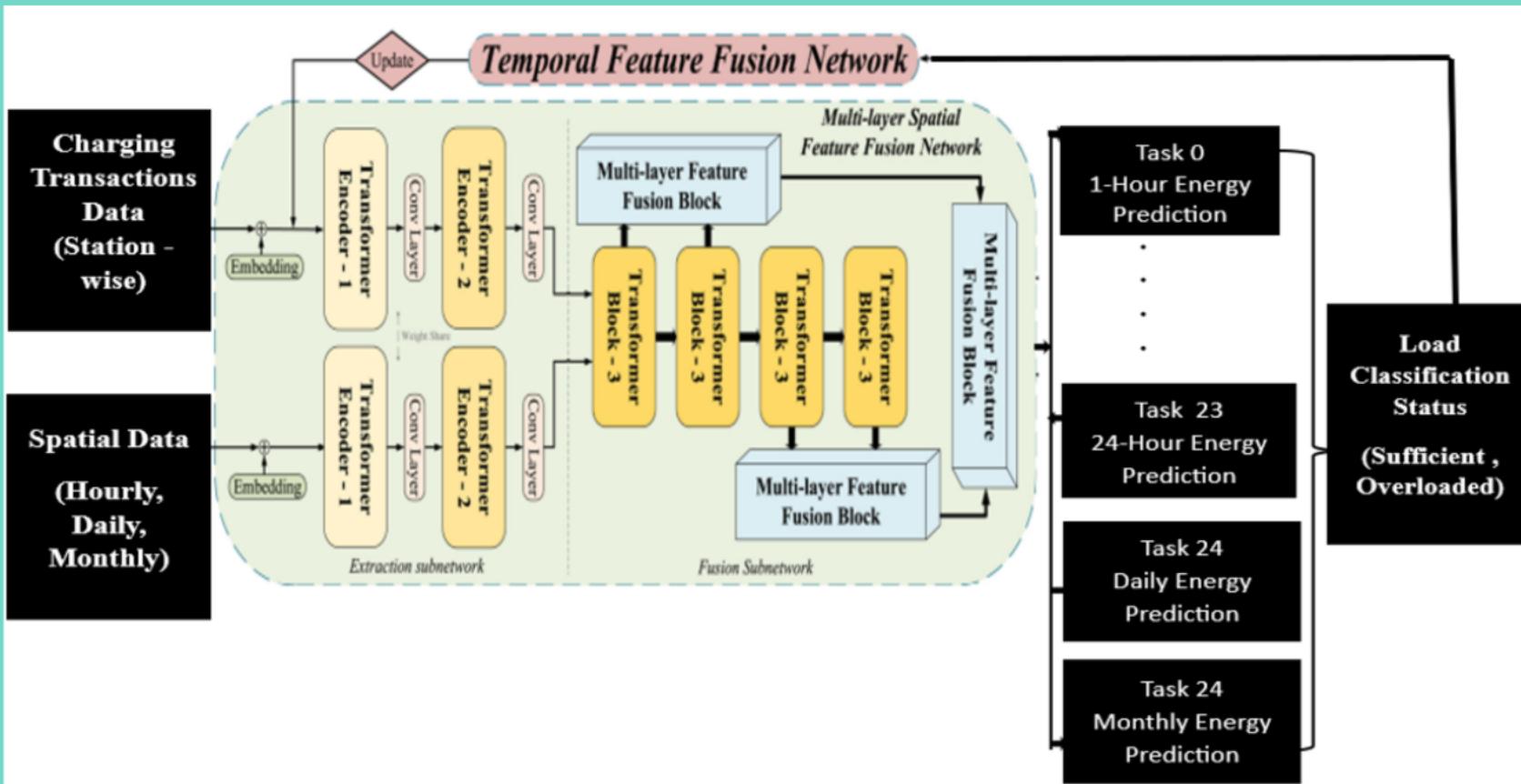
Improved



PREDICTING SHORT AND LONG - TERM ENERGY DEMAND

Temporal Fusion Transformer Model (TFT) Architecture : Improvements

To Predict short term energy demand like hourly and long term enegry demand like weekly, monthly for each charging station.



1

Fine-tuned the HistGradientBoosting Regressor model, for optimal performance

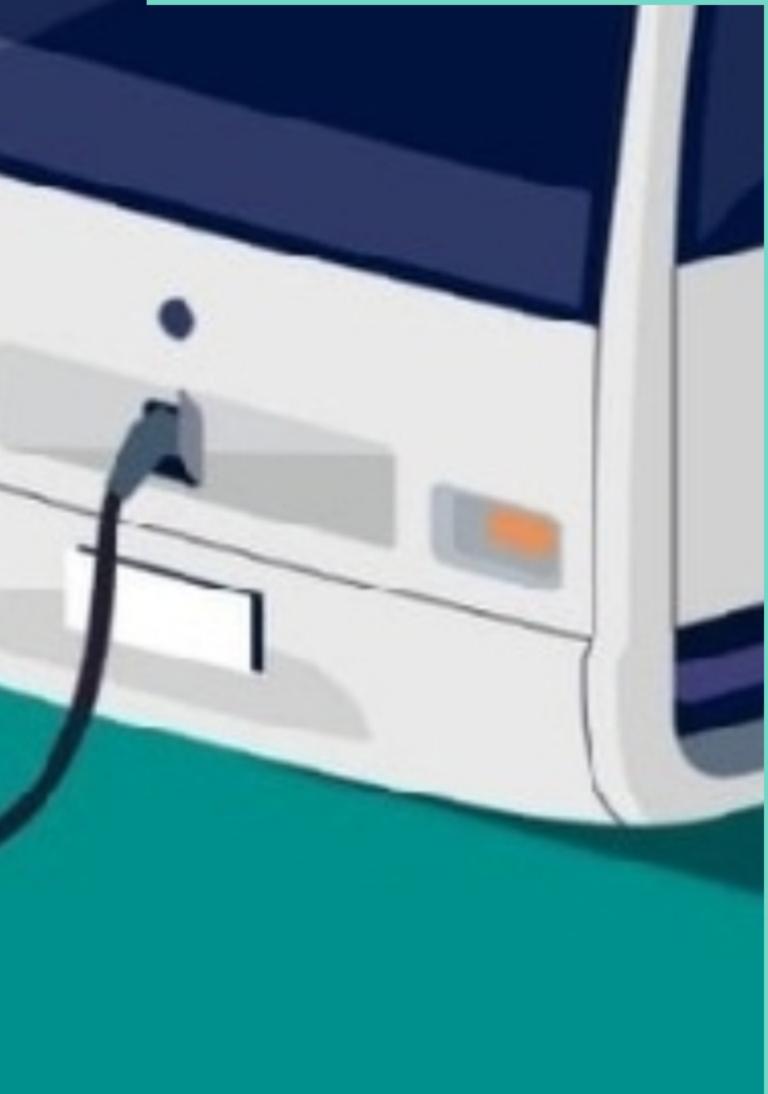
2

Robust imputation strategy using the median instead of mean imputation.

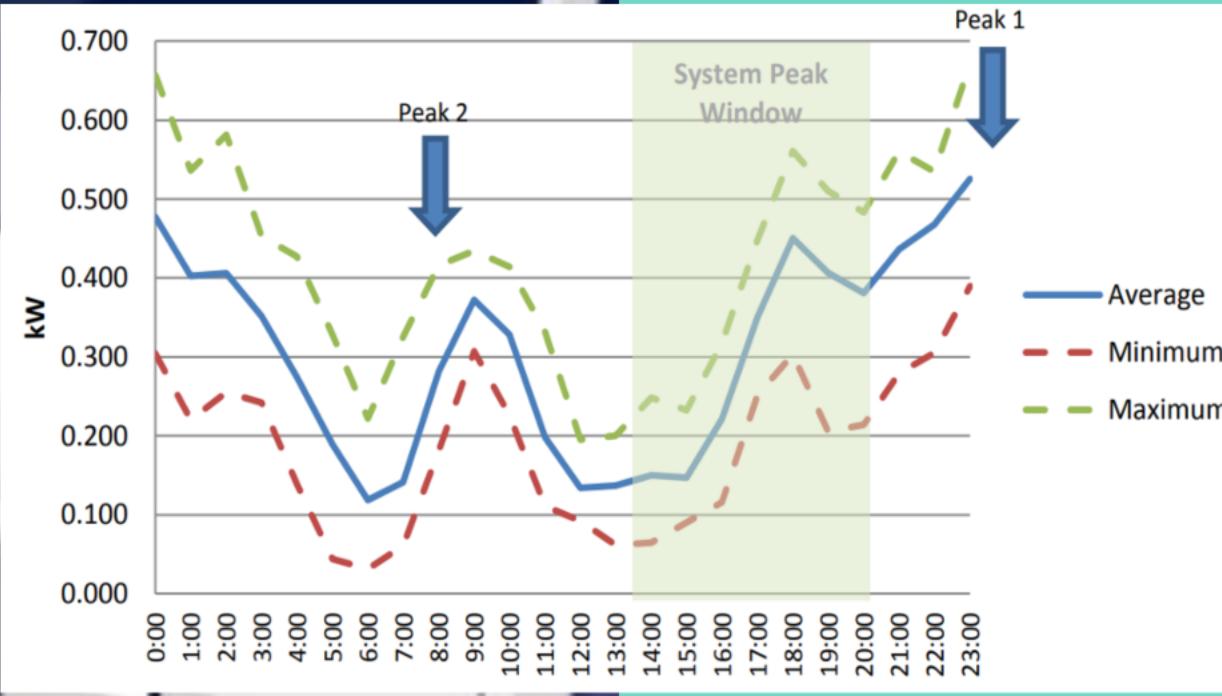
3

Identified and utilized key features such as 'Average_Power', 'Max_Power', 'Starting_SOC', and 'Charging_Duration' for forecasting to enhance model accuracy.

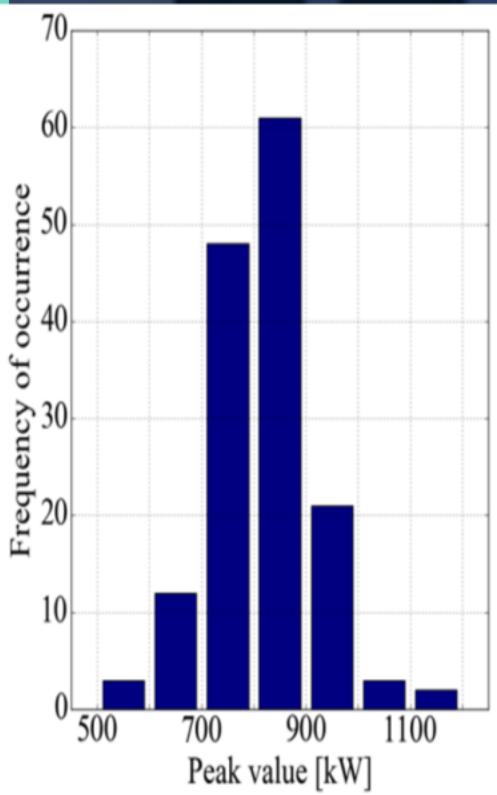
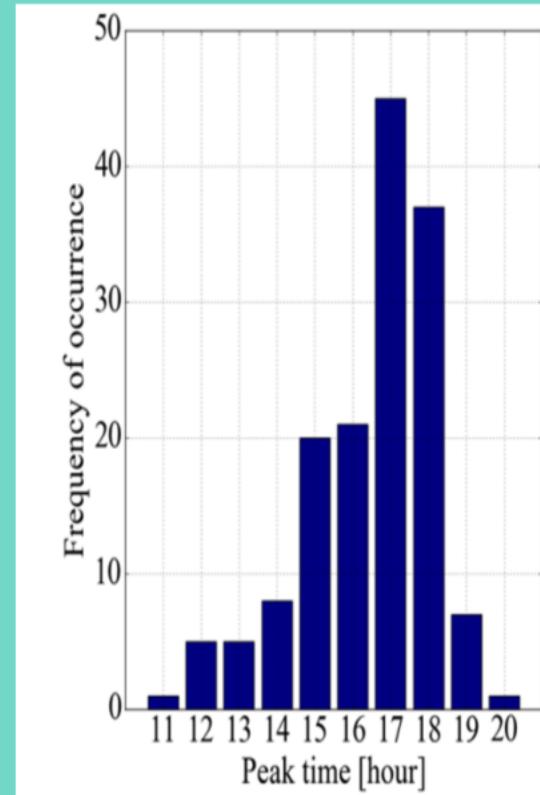
Energy Demand Prediction for a Charging Station



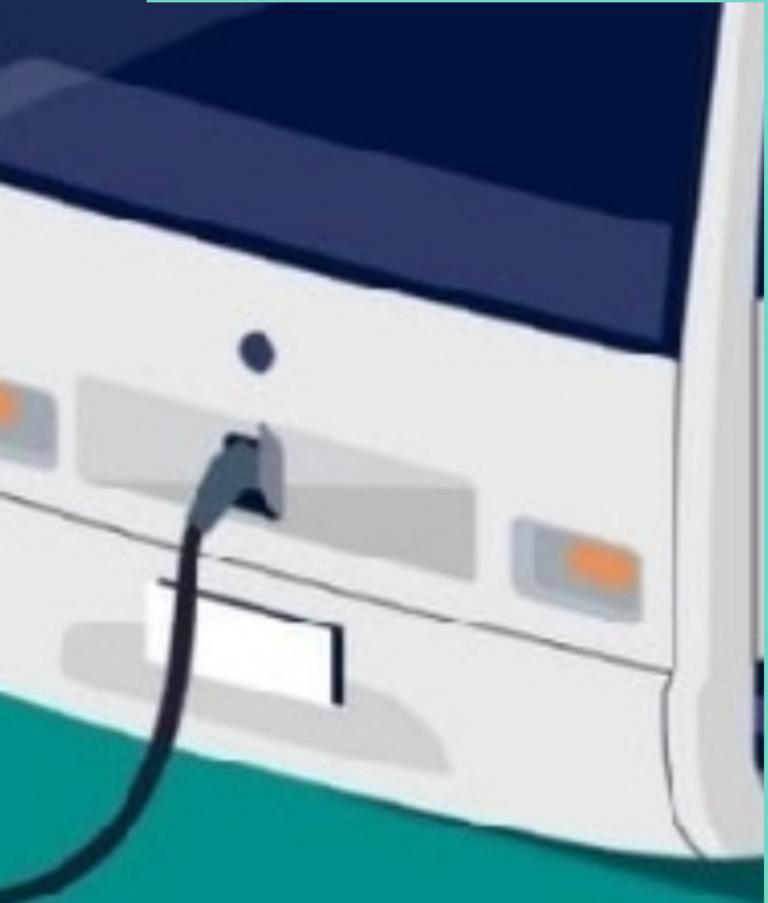
Energy Demand Prediction for a Charging Station



Improved



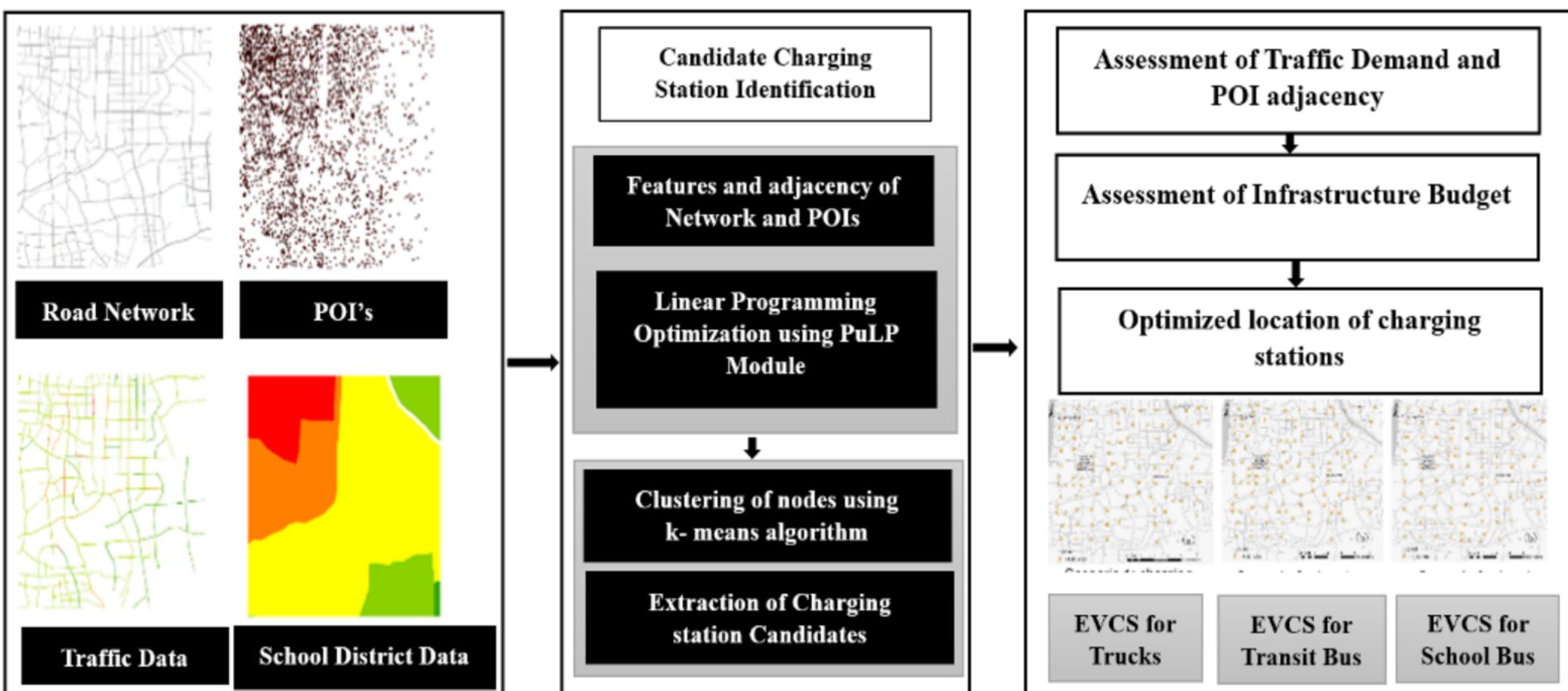
Energy Demand Prediction for a Charging Station



OPTIMAL PLACEMENT OF NEW CHARGING STATIONS FOR EACH VEHICLE TYPE

Linear Programming and Clustering Model Architecture

To identify optimal locations for placing new charging stations for each type of vehicle using the point of interest related to them utilizing Pulp library linear programming and K-Means Clustering model.



Optimal Locations for New EV Charging Stations- San Jose

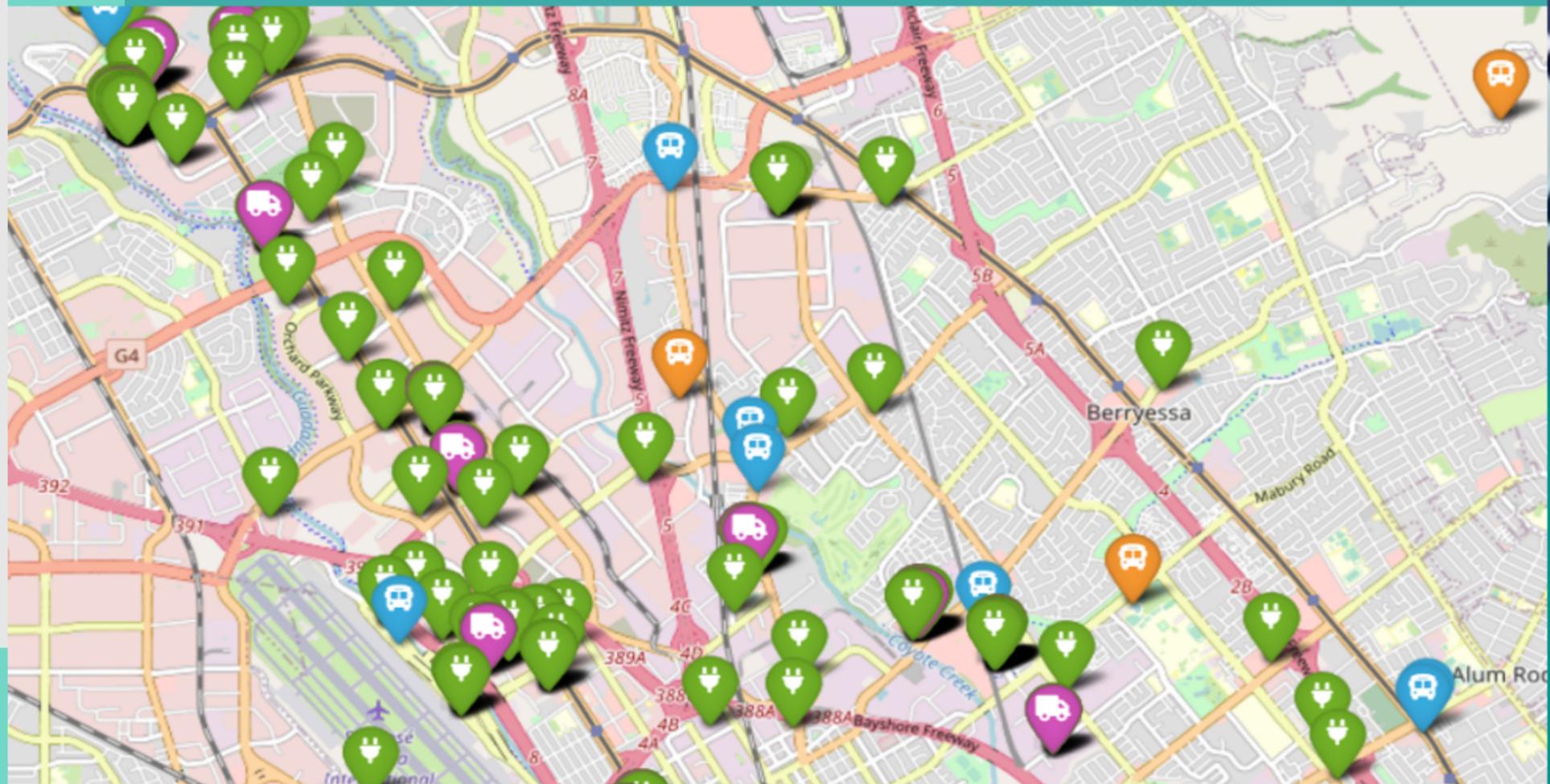
Green- Existing EV charging Stations

Blue- Suggested Charging Station Location for Transit Bus

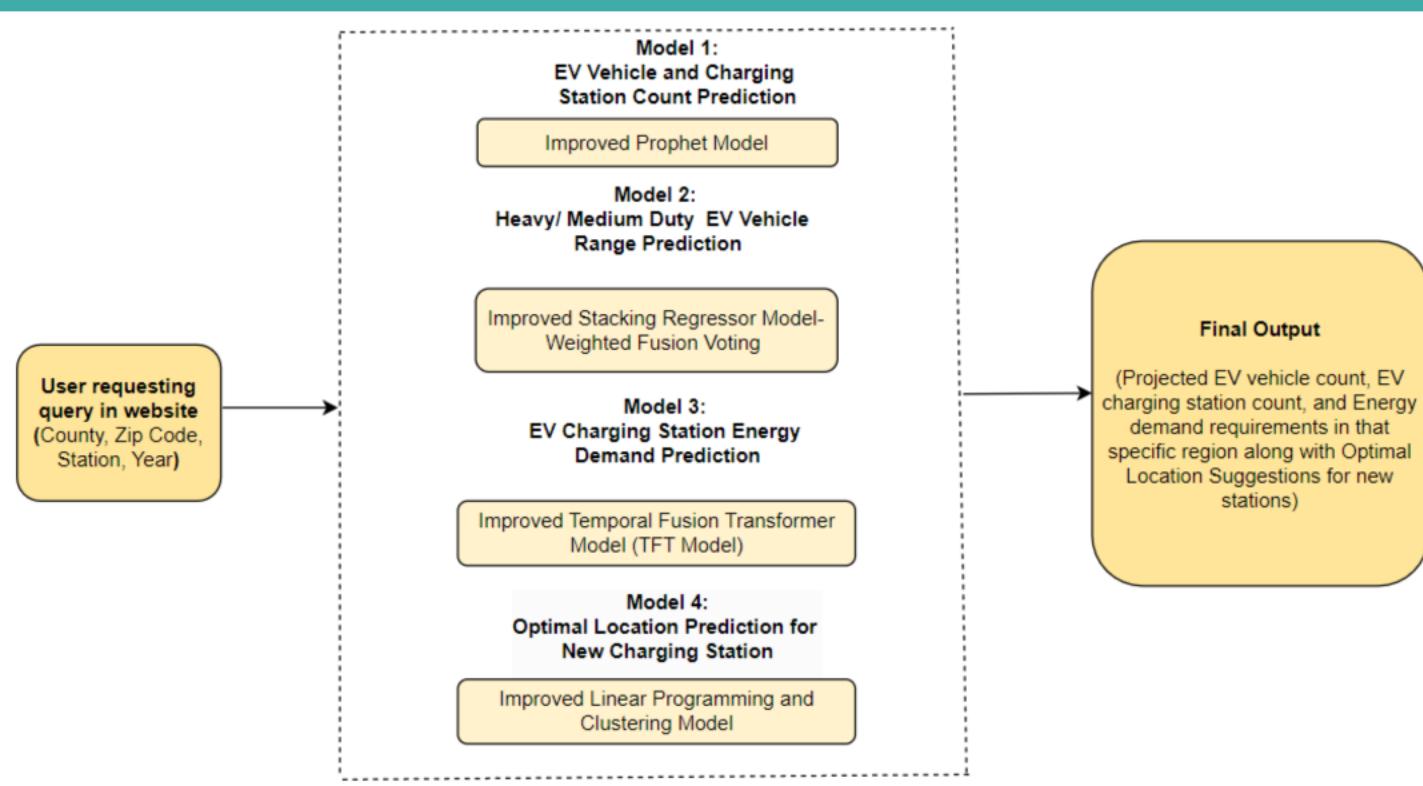
Orange- Suggested Charging Station Location for School Bus

Purple- Suggested Charging Station Location for Delivery Truck

Improved



Machine Learning Modeling : Innovation



- Prophet dynamically adjusts to irregularities, ensuring accurate predictions even in the presence of outliers
- The use of precision-weighted fusion in the Stacking Ensemble Regressor model optimally combines predictions from individual models, assigning higher weights to more accurate models.
- The Temporal Fusion Transformer (TFT) Model's innovation lies in its ability to effectively handle temporal dependencies in EV charging station energy demand prediction which captures intricate temporal patterns
- The integration of PuLP linear programming optimization in the Optimal Location Prediction model, coupled with K-means clustering, ensures that the placement of new charging stations is not only data-driven but also optimized for cost-effectiveness and resource utilization.

Machine Learning Modeling : Comparision



Characteristic	Prophet	Stacking Ensemble Regressor	Temporal Fusion Transformer	PuLP Linear Programming with K-means Clustering
Targeted Problems	EV Vehicle and Charging Station Count Prediction EV Vehicle Range Prediction	Heavy/Medium Duty EV Vehicle Demand Prediction	EV Charging Station Energy Demand Prediction	Optimal Location Prediction for New Charging Station
Input	Electric Vehicle Registrations	Medium/Heavy Duty EV Transactions	Medium/Heavy Duty EV Transactions	EV Charging Station ,Traffic Data, Point of Interests, School and Transit Bus Network
Output	Projected Count of EV in each Zip Code	Predicted Range of EV	Short and Long term demand prediction of Energy	Optimal Location Suggestions for EV Charging station
Data Type	Discrete	Continuous	Continuous and Categorical	Continuous
Approaches	Time Series Decomposition	Ensemble Learning	Sequence-to-Sequence Model	Linear Programming + Clustering
Computational Complexity	Low	Moderate	High	Moderate to High
Strengths	Seasonality Patterns	Ensemble Synergy	Temporal Dependencies	Spatial Optimization

Model Evaluation Metrics

Model Improvement Comparison

Feature	Vehicle Type	Model	Time Frame	Previous results				Current results				
				MSE	MAE	RMSE	R ²	MSE	MAE	RMSE	R ²	
EV Demand Forecast	Heavy/Medium Duty Vehicles	Prophet	Yearly	12.75	11.69	26.87	0.87	10.55	9.85	25.93	0.89	
EV Range Prediction	Transit Bus	Weighted Fusion Meta Regressor Model	On Demand	9.063	9.874	88.113	0.75	8.076	8.50	88.007	0.75	
	School Bus			8.947	9.113	87.248	0.76	8.57	9.037	86.23	0.77	
	Delivery Truck			11.345	12.278	83.903	0.82	10.23	11.67	81.45	0.84	
EV Energy Demand prediction	Transit Bus	Temporal Fusion Transformer	Daily	0.828	0.957	4.36	0.93	0.798	0.916	4.25	0.93	
			Weekly	1.794	1.897	9.36	0.91	1.689	1.862	9.043	0.91	
			Monthly	0.984	0.932	7.64	0.91	0.761	0.873	7.54	0.91	
	School Bus		Daily	0.865	0.847	5.96	0.92	0.757	0.82	5.02	0.93	
			Weekly	0.897	0.828	4.98	0.92	0.763	0.811	4.96	0.93	
			Monthly	1.895	1.952	9.68	0.90	1.883	1.94	9.05	0.91	
	Delivery Truck		Daily	2.969	2.643	12.36	0.88	2.619	2.531	10.67	0.89	
			Weekly	2.453	2.387	11.97	0.89	2.35	2.053	11.99	0.89	
			Monthly	2.874	2.775	13.01	0.88	2.853	2.766	12.93	0.88	

Metric results

Metric	Station - Wise	Site - Wise	Zip Code - Wise
Mean Squared Error (MSE)	2.453	1.895	1.348
Mean Absolute Error (MAE)	2.387	1.952	1.652
Root Mean Square Error (RMSE)	11.97	9.68	6.942
R-squared (R2)	0.89	0.91	0.93
Clustering Accuracy	87%	92%	95%
Precision	0.85	0.89	0.94
Recall	0.88	0.92	0.96
F1-score	0.86	0.90	0.95

Forecast of EV Vehicles Count on Road - Zip Code Wise

Year 2024: Projected EV Vehicle Count = 4041
Year 2025: Projected EV Vehicle Count = 4695
Year 2026: Projected EV Vehicle Count = 5291
Year 2027: Projected EV Vehicle Count = 5896
Year 2028: Projected EV Vehicle Count = 6529
Year 2029: Projected EV Vehicle Count = 7201
Year 2030: Projected EV Vehicle Count = 7781
Year 2031: Projected EV Vehicle Count = 8379
Year 2032: Projected EV Vehicle Count = 9018
Year 2033: Projected EV Vehicle Count = 9706
Year 2034: Projected EV Vehicle Count = 10271
Year 2035: Projected EV Vehicle Count = 10863

	Year	Zip_Code	Vehicle_Count
0	2015-01-01	94124	230
1	2015-01-01	90813	48
2	2015-01-01	90640	22
3	2015-01-01	90247	21
4	2015-01-01	90249	13
5	2016-01-01	94124	290
6	2016-01-01	92805	71
7	2016-01-01	91405	49
8	2016-01-01	93534	46
9	2016-01-01	94305	45
10	2017-01-01	94124	288
11	2017-01-01	92805	97
12	2017-01-01	91405	49
13	2017-01-01	94305	43
14	2017-01-01	95816	34
15	2018-01-01	94606	26
16	2018-01-01	93108	18
17	2018-01-01	93603	16
18	2018-01-01	92286	15
19	2018-01-01	92599	15
20	2019-01-01	94124	322
21	2019-01-01	90012	103
22	2019-01-01	93534	64
23	2019-01-01	92805	50
24	2019-01-01	95660	42
25	2020-01-01	93517	30
26	2020-01-01	94580	27
27	2020-01-01	93103	26
28	2020-01-01	95117	26
29	2020-01-01	94141	23
30	2021-01-01	94124	298
31	2021-01-01	90012	97
32	2021-01-01	93625	51
33	2021-01-01	92806	35
34	2021-01-01	94928	33
35	2022-01-01	92101	1115
36	2022-01-01	90012	611
37	2022-01-01	95812	159
38	2022-01-01	94124	122
39	2022-01-01	94612	112

Actual and Predicted Values of Energy

- Station Wise

	Actual value	Predicted value	Difference
3286	20.0	21.16	-1.16
576	93.0	84.60	8.40
1053	36.0	36.62	-0.62
1240	19.0	19.20	-0.20
1834	20.0	20.00	0.00
...
447	68.0	79.96	-11.96
869	128.0	89.84	38.16
1271	172.0	179.72	-7.72
2463	19.0	19.30	-0.30
531	45.0	85.82	-40.82

Station Name: WEBSTER #3
Date: 2020-09-20
Daily Demand (kwh): 40.507
Number of Vehicles Charged: 1
Load Status: Overloaded

Predicted Values of Energy with confidence intervals - Zip Code Wise

Zip Code: 94306

Date: 2020-09-20

Daily Demand (kwh): 178.85

Load Status: Overloaded



	Lower Confidence Interval	Upper Confidence Interval	Predictions
2021-06-30	2116.0	2147.0	2131.0
2021-07-31	2148.0	2206.0	2177.0
2021-08-31	2178.0	2270.0	2224.0
2021-09-30	2204.0	2334.0	2269.0
2021-10-31	2228.0	2400.0	2314.0
2021-11-30	2249.0	2466.0	2358.0
2021-12-31	2268.0	2533.0	2401.0
2022-01-31	2285.0	2601.0	2443.0
2022-02-28	2300.0	2669.0	2485.0
2022-03-31	2314.0	2738.0	2526.0
2022-04-30	2325.0	2806.0	2566.0
2022-05-31	2335.0	2875.0	2605.0
2022-06-30	2344.0	2945.0	2644.0
2022-07-31	2350.0	3014.0	2682.0
2022-08-31	2356.0	3083.0	2720.0
2022-09-30	2360.0	3153.0	2756.0
2022-10-31	2363.0	3222.0	2793.0
2022-11-30	2365.0	3292.0	2828.0
2022-12-31	2365.0	3361.0	2863.0

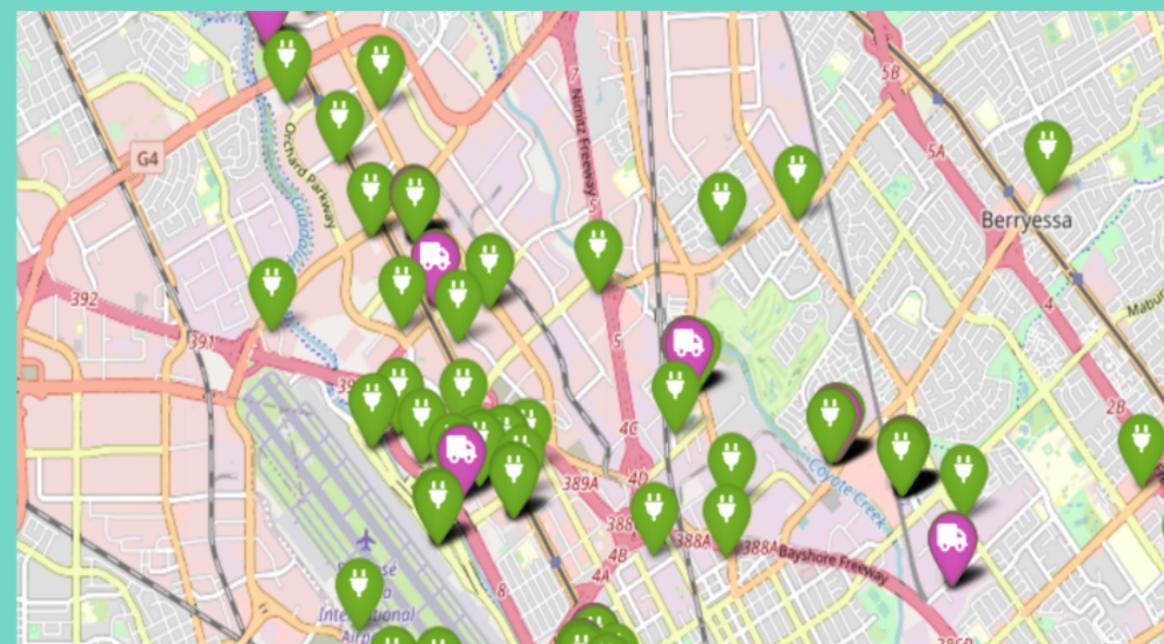
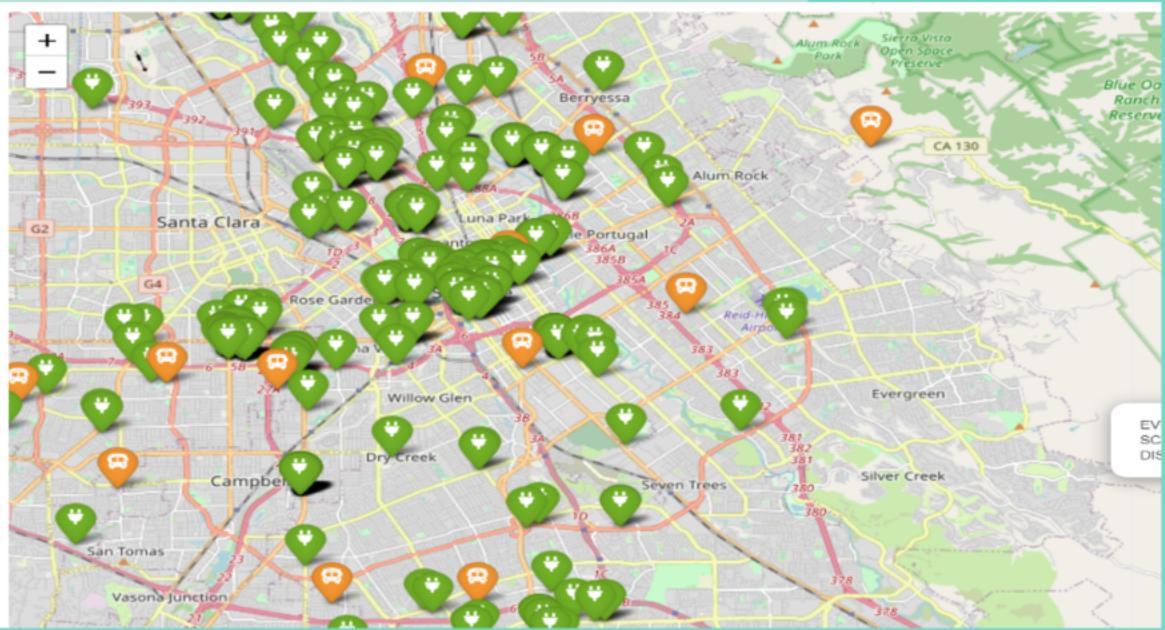
Optimal Locations for New EV Charging Stations- San Jose

Green- Existing EV charging Stations

Blue- Suggested Charging Station Location for Transit Bus

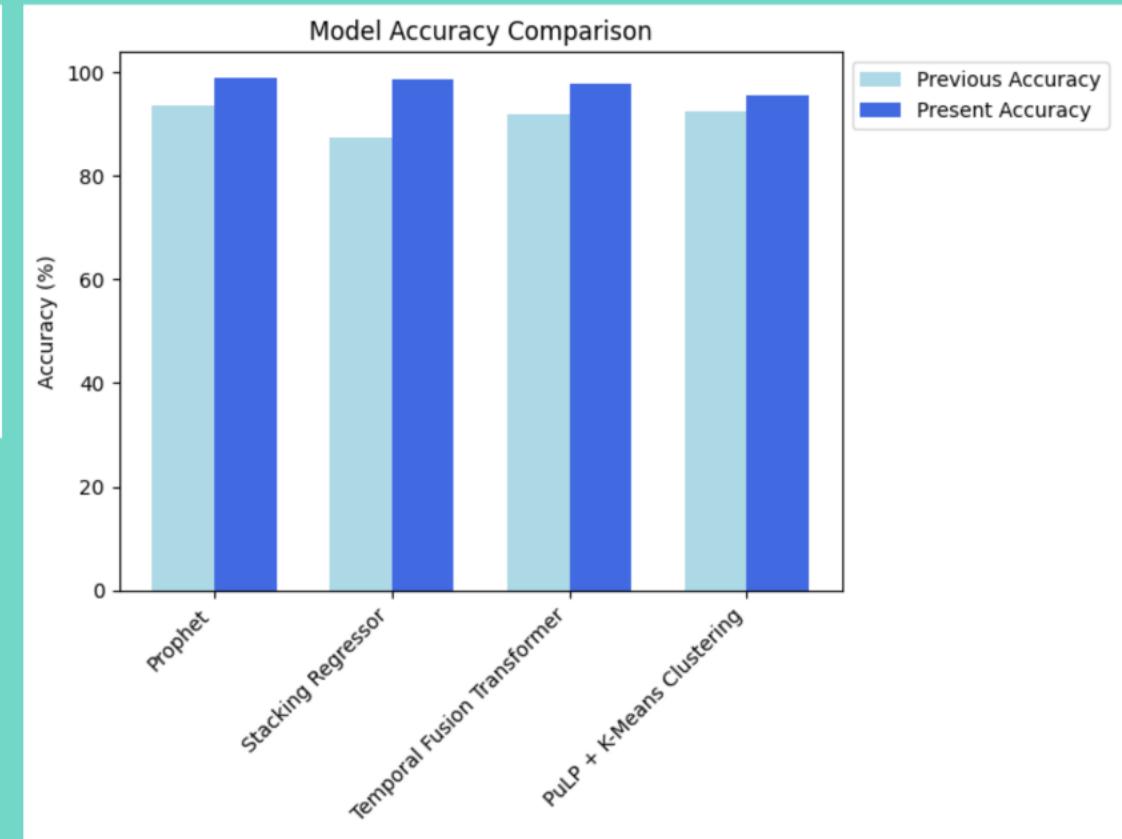
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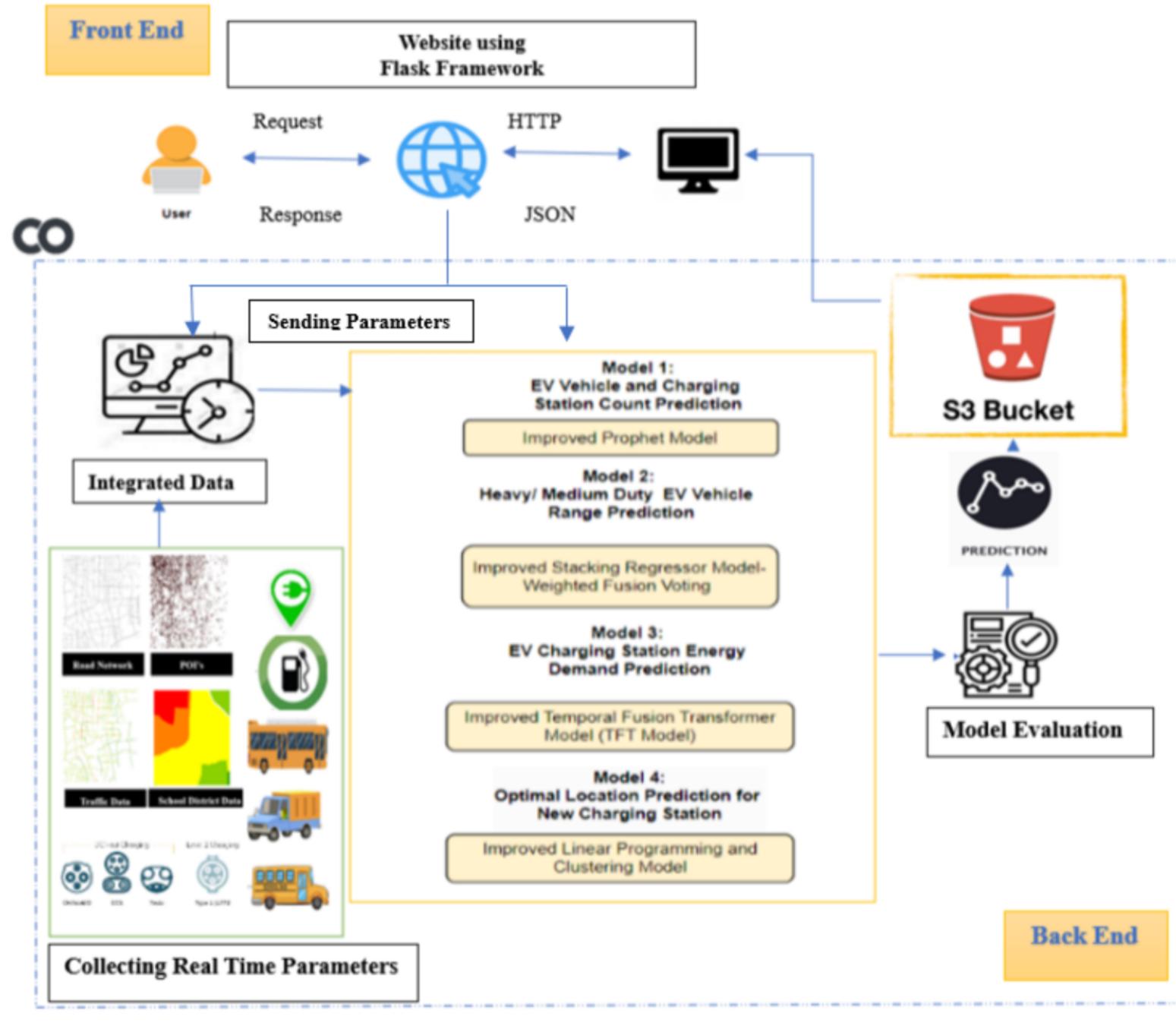


Improvement Summary for all Models

Run Time performance Comparision		
Feature	Device Specifications	Average Run Time (Seconds)
Forecasting future Medium/ Heavy Duty EV count on road	HP Pavilion Laptop Processor: 10th Generation Intel® Core™ i5 Memory: 16GB DDR4-2666 SDRAM	0.359
Predicting EV Range		0.056
Long and Short Term Energy Demand Prediction		0.981
Optimal Location Suggestion for new EV charging station		1.482
Integrated System		0.862



SYSTEM ARCHITECTURE



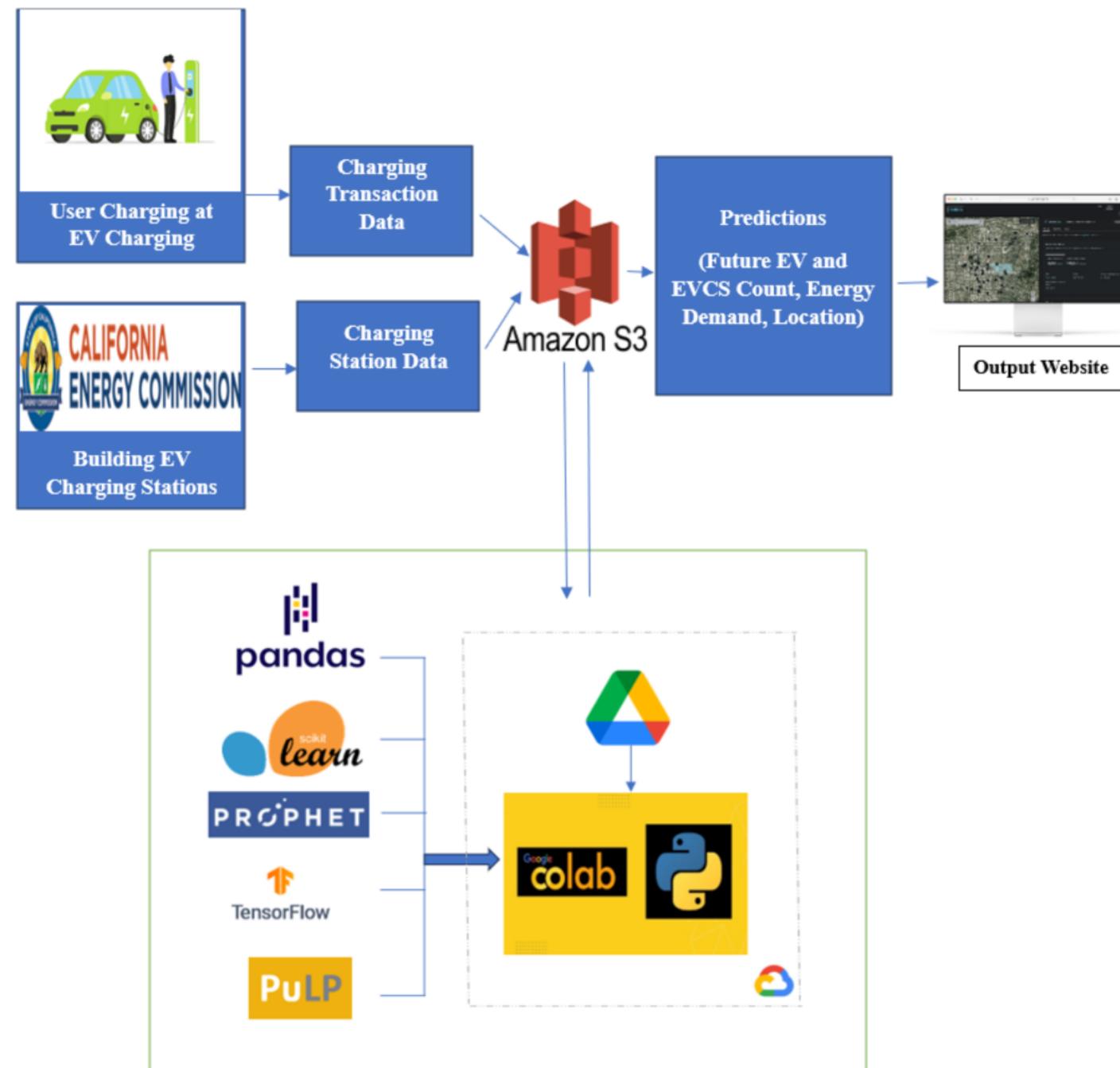
Intelligent Solution Development

Database Management

For Storing EV Charging related data and the generated predictions : AWS S3

Supporting Platforms and Cloud Environments

Model Development : pandas, scikit-learn, TensorFlow, Prophet, PuLP, Google Colab, GCP



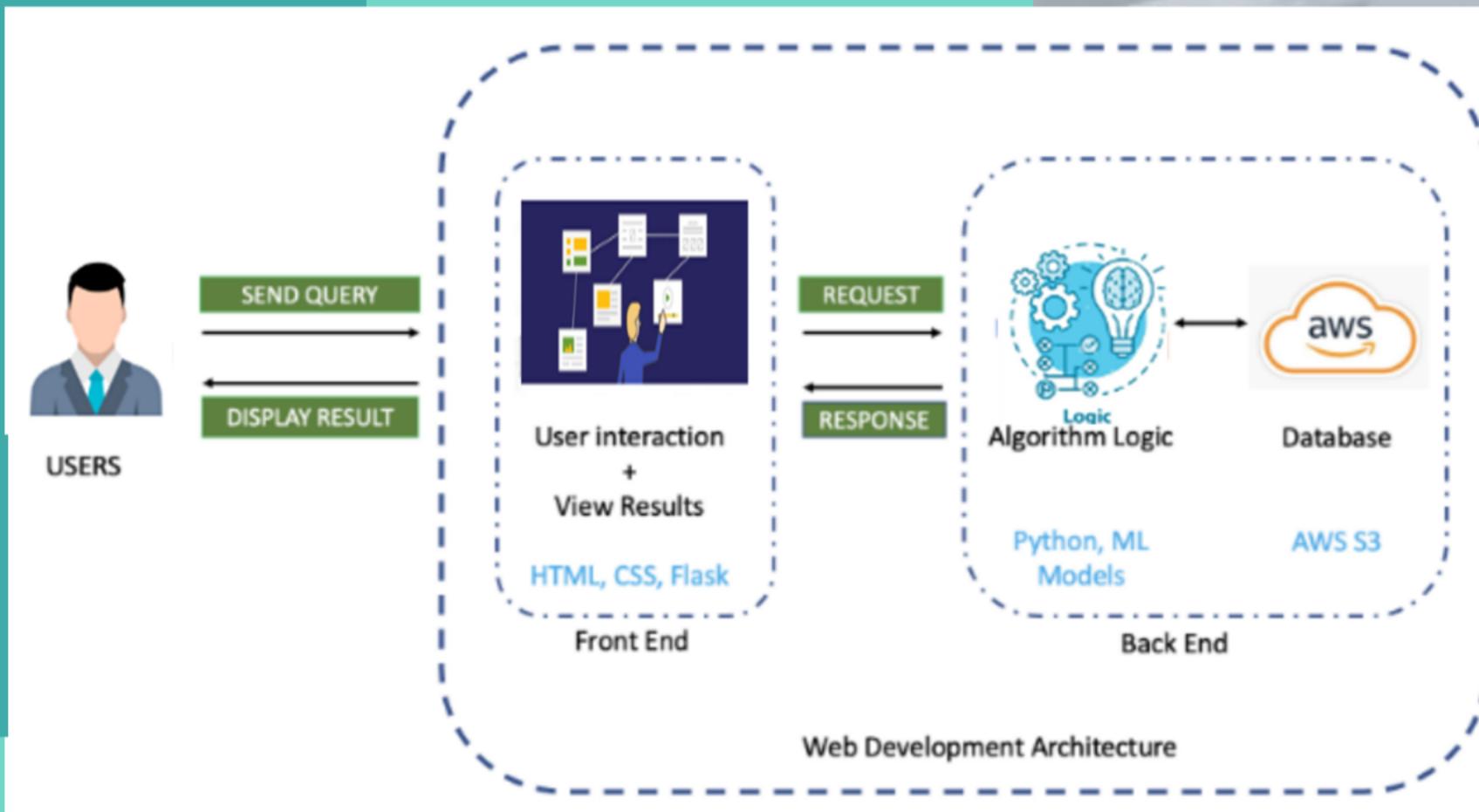
WEB DEVELOPMENT INFRASTRUCTURE

Front End

- *GUI: web page displaying real-time EV details with HTML, CSS and JavaScript*
- *Response : AWS S3 HTTP response*
- *Web Framework: All modules are integrated using Flask*

Back End

- *Database : AWS S3*
- *Algorithm : Python ML libraries and packages*



SYSTEM IMPLEMENTATION

Navigation Bar(GitHub,
Dashboard etc.,)

The screenshot shows the 'VELOCITY' web application interface. At the top, there is a dark header bar with the title 'VELOCITY' and a navigation bar containing links for HOME, ABOUT, CONTACT US, DASHBOARD, and GITHUB. A callout arrow points from the text 'Navigation Bar(GitHub, Dashboard etc.,)' to the GITHUB link in the header. Below the header, a teal-colored banner contains the text: 'Vehicle Estimations and Location Insights for EV Charging Optimization (VELOCITY). This platform streamlines EV charging optimization, offering detailed analytics for heavy/medium-duty vehicles, and suggesting strategic new station locations on an interactive map'. Underneath the banner, there are three buttons: 'Charging Census' (disabled), 'Charging Snapshot' (disabled), and 'Charge Map' (disabled). The main content area features two large cards. The left card is titled 'How Much Electric Vehicle Charging Do I Need in My Area?' and contains a map of California divided into county-level regions. It is labeled 'County Wide' and has a 'Get Estimates' button. The right card is also titled 'How Much Electric Vehicle Charging Do I Need in My Area?' and contains a map of a specific geographic area divided into zip code regions, with several zip codes labeled (92585, 92545, 92587, 92584). It is labeled 'Zipcode Wide' and has a 'Get Estimates' button.

SYSTEM IMPLEMENTATION

127.0.0.1:5000/home

VELOCITY

HOME ABOUT CONTACT US DASHBOARD GITHUB

Charging Census Charging Snapshot Charge Map

Alameda 2027 Calculate

Drop Down Box to select Region

Drop Down Box to select Year

The screenshot shows the Velocity system's main interface. At the top, there is a navigation bar with links for HOME, ABOUT, CONTACT US, DASHBOARD, and GITHUB. Below the navigation bar, there are three buttons: Charging Census, Charging Snapshot, and Charge Map. A dropdown menu is open, showing the option "Alameda". To the right of the dropdown is a year selector dropdown set to "2027" and a green "Calculate" button. Below these controls is a map of California divided into counties, each colored differently. Two arrows point from the text labels "Drop Down Box to select Region" and "Drop Down Box to select Year" to the respective dropdown menus.

VELOCITY

HOME ABOUT

Charging Census Charging Snapshot Charge Map

What kinds of charging ports are needed?

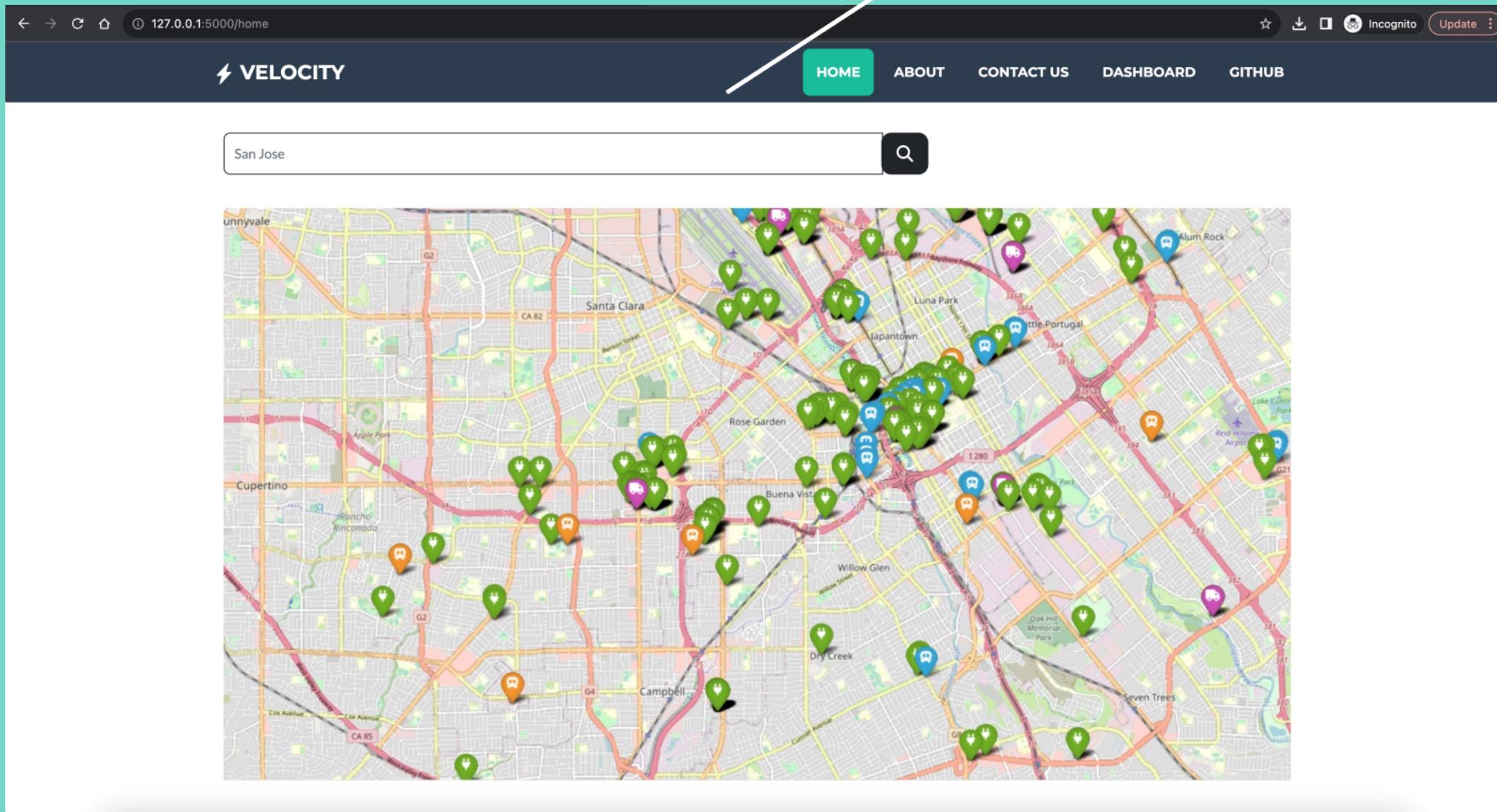
59826	Number of Vehicles	
46	Shared Private DC Fast Charging	
2861	Shared Private Level 2 Charging	
497	Public DC Fast Charging	
1868	Public Level 2 Charging	

This screenshot shows the results of the charging needs calculation. It lists five categories: Number of Vehicles (59826), Shared Private DC Fast Charging (46), Shared Private Level 2 Charging (2861), Public DC Fast Charging (497), and Public Level 2 Charging (1868). Each item is accompanied by a small icon representing the type of charging port.

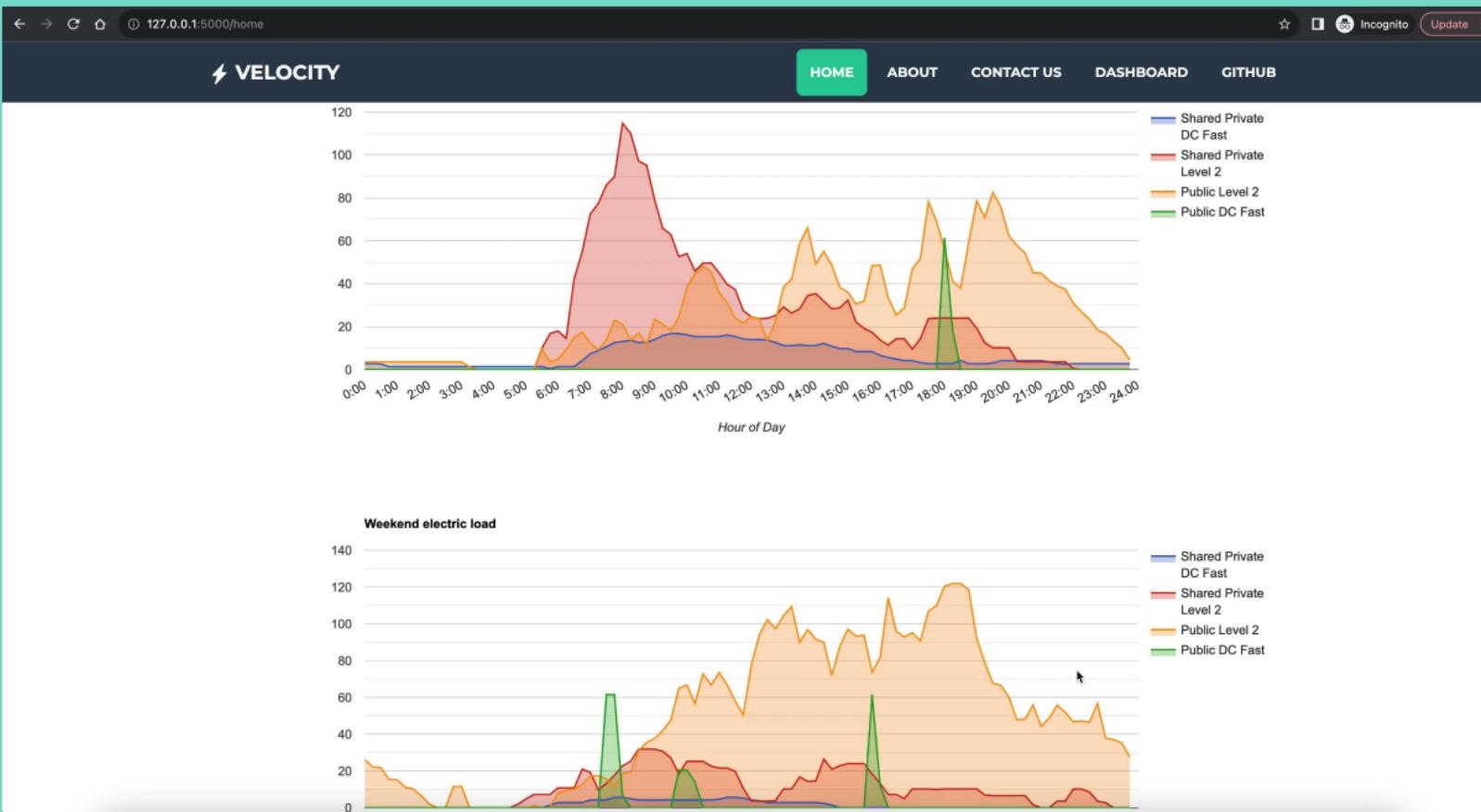
SYSTEM IMPLEMENTATION

Search Box

Map displaying existing EV charging stations and newly proposed locations for San Jose



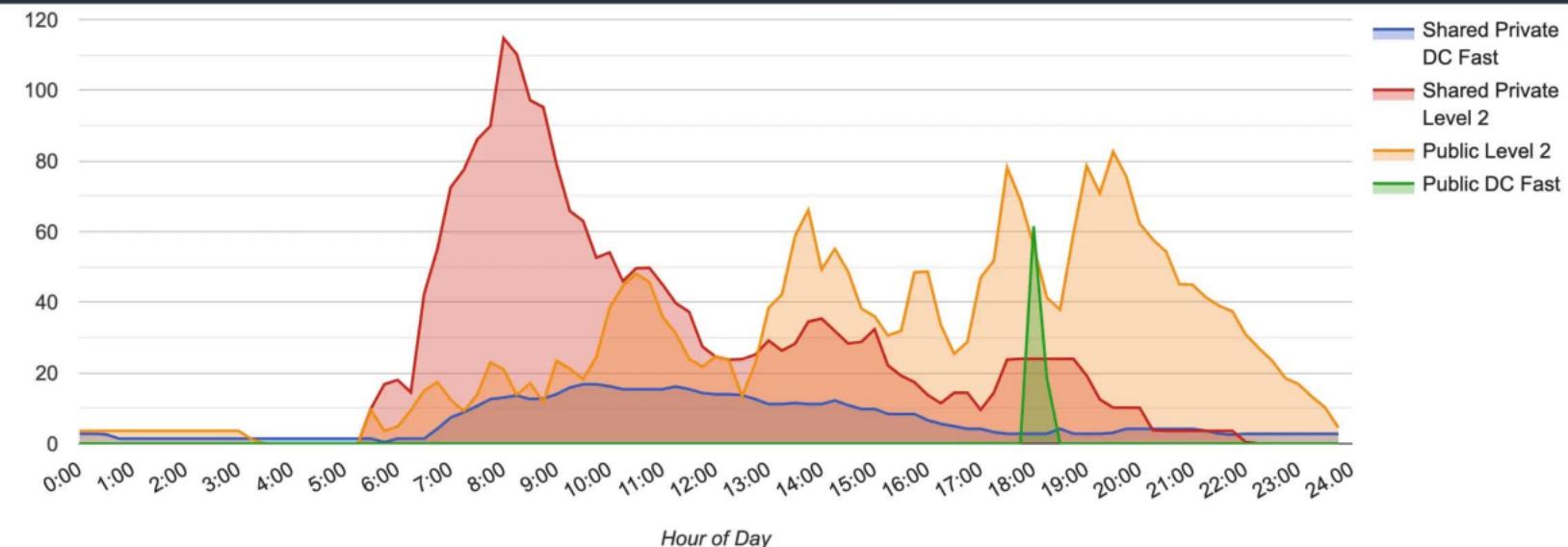
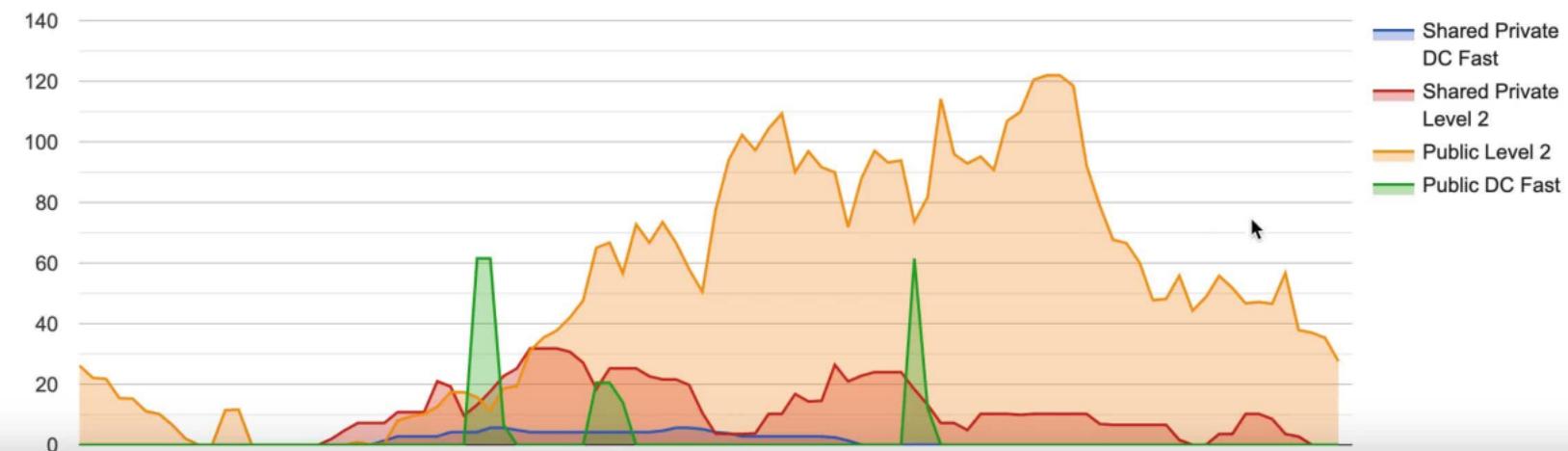
SYSTEM DEMO



Link : <https://velocity-app-5b2dc0abb830.herokuapp.com/>

Scenarios Tested:

- Region Specific Future Charging Station Demand
- Region Specific Energy Demand snapshot
- Newly propose charging station locations for Transit Bus, School Bus and Delievry Truck in San Jose

**Weekend electric load**



THANK YOU

Data Driven Analysis of EV Charging Infrastructure - Medium/Heavy duty Vehicles



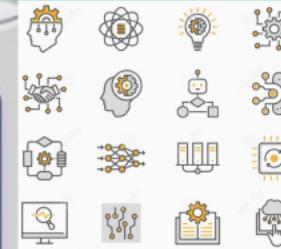
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Web system design and development



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