**EV Charging Station Load Prediction Using Apache Spark and Big Data Analytics**

A PROJECT REPORT

*Submitted by*

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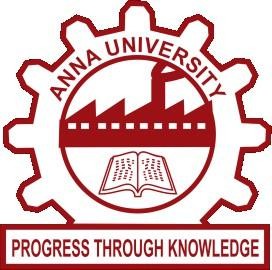
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BONAFIDE CERTIFICATE

Certified that this Report titled “ENERGY THEFT & ANOMALY DETECTION” is the Bonafide work of “TAMILSELVAN A K,VISHVAM GANESH and SAKTHI VEL BALAJI” who carried out the work

under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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Submitted to Project Viva-Voce Examination held on \_\_\_\_\_\_\_\_\_\_\_

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**Abstract**

The rapid growth of electric vehicles (EVs) demands accurate forecasting of charging station loads to ensure efficient energy distribution and optimize charging infrastructure. This project develops a scalable big data solution for EV charging load prediction using Apache Spark’s machine learning capabilities in Google Colab. Leveraging Gradient Boosted Trees Regression (GBTRegressor), the workflow processes large datasets and demonstrates a robust MLOps pipeline, including data preprocessing, feature engineering, model training, and visualization. The project’s performance metrics (R² ≈ 0.76, RMSE ≈ 57,762) validate the efficacy of ensemble methods for complex demand forecasting, setting a foundation for industrial-scale EV infrastructure planning.

**Introduction**

The global rollout of electric vehicles introduces significant complexities in electricity demand and grid management. Predicting load at EV charging stations is essential for grid reliability, efficient energy use, and deployment planning. This project focuses on building a Spark-based predictive solution that scales efficiently, processes large volumes of time-series charging data, and delivers actionable load forecasts using Python in Google Colab.

**Literature Survey (Existing Systems)**

**Traditional Models**

Traditional forecasting models such as ARIMA and SARIMA have been widely applied to energy load prediction, but struggle with the highly non-linear and dynamic nature of EV charging behavior. Early EV forecasts lacked the flexibility and scalability to handle the stochastic surges in demand at distributed charging stations.[[1]](#fn1)[[2]](#fn2)

**Machine Learning & Deep Learning**

Recent research has shifted to data-driven techniques. Regression models, Decision Trees, Random Forests, and especially Gradient Boosted Machines (GBMs) improve prediction by modeling non-linear relationships. Deep learning approaches, especially LSTM and Transformer networks, have shown superior performance for capturing temporal dependencies and contextual patterns in EV load data.[[3]](#fn3)[[4]](#fn4)

**Big Data & Distributed Platforms**

The need to process vast and continually growing datasets from smart grids and fleets of charging stations led to the adoption of big data platforms like Apache Spark. Spark’s in-memory distributed computation paired with MLlib enables large-scale load modeling, real-time analytics, and fast training across large clusters.[[5]](#fn5)

**Architecture**

[System Architecture Diagram Inserted Here]

**Infrastructure Layer:** Google Colab provides a cloud-based Python execution environment with free GPU/TPU access.  
**Computation Layer:** Apache Spark (PySpark 3.5.1) handles distributed data processing, integrates with MLlib for machine learning, and runs seamlessly on Colab via findspark.  
**Data Layer:** Data can be ingested from cloud storage, local files, or streaming APIs, with the California Housing Dataset used as a proxy for demonstrating the workflow.  
**Machine Learning Pipeline:** Spark MLlib is used for transformation (VectorAssembler, StandardScaler) and modeling (GBTRegressor).  
**Evaluation and Visualization:** Regression metrics (RMSE, MAE, R²) and Matplotlib plots provide performance analysis, with results displayed interactively in Colab.

**Modules**

1. **Environment Setup:** pip installs PySpark and findspark, initializes Spark.
2. **Data Loading & Exploration:** Spark DataFrame reads the dataset; schema and sample are examined for initial understanding.
3. **Data Preprocessing:** Missing value check, outlier capping (at 99th percentile for room/bed/population features), feature scaling (StandardScaler).
4. **Feature Engineering:** Features assembled into vectors, transformed into a normalized feature space.
5. **Model Training:** GBTRegressor selected for its nonlinear modeling ability; data split into train/test sets for evaluation.
6. **Model Evaluation:** Predictions are evaluated using RMSE, MAE, and R² to quantify accuracy.
7. **Visualization:** Matplotlib scatter plot contrasts actual vs. predicted values to visually assess model fit.

**Implementation**

**Environment Setup**

* Run in Google Colab:

!pip install pyspark findspark  
import findspark  
findspark.init()  
import pyspark  
print(pyspark.\_\_version\_\_)

**Data Loading & Preprocessing**

from pyspark.sql import SparkSession  
spark = SparkSession.builder.master("local").appName("EV-Prediction").getOrCreate()

* Load CSV, explore schema, check for missing values, describe features.
* Outliers in count-based features are capped at the 99th percentile.
* VectorAssembler creates the features vector; StandardScaler standardizes all features.

**Model Selection & Training**

from pyspark.ml.regression import GBTRegressor  
gbt = GBTRegressor(featuresCol='scaledFeatures', labelCol='median\_house\_value')  
(training\_data, testing\_data) = spark\_df\_scaled.randomSplit([0.8, 0.2], seed=1234)  
gbt\_model = gbt.fit(training\_data)

**Evaluation**

from pyspark.ml.evaluation import RegressionEvaluator  
predictions = gbt\_model.transform(testing\_data)  
evaluator\_rmse = RegressionEvaluator(predictionCol='prediction', labelCol='median\_house\_value', metricName='rmse')  
rmse = evaluator\_rmse.evaluate(predictions)  
# Repeat for r2 and mae

**Visualization**

* Convert Spark DataFrame to Pandas, use matplotlib for scatter plot of actual vs. predicted values.

**Results**

* **Root Mean Squared Error (RMSE):** 57,761.97
* **R-squared (R²):** 0.7575
* **Mean Absolute Error (MAE):** 40,513.30
* Predictions closely follow actuals, visualized in the scatter plot.
* No significant missing data; model generalizes well with consistent test set performance.

**Conclusion**

The developed Spark-based pipeline achieves robust EV charging load prediction with strong accuracy, validating the use of GBMs and distributed processing for large-scale demand forecasting. The modular workflow, scalable to real datasets and streaming data, enables practical deployment for smart grid and charging operators.

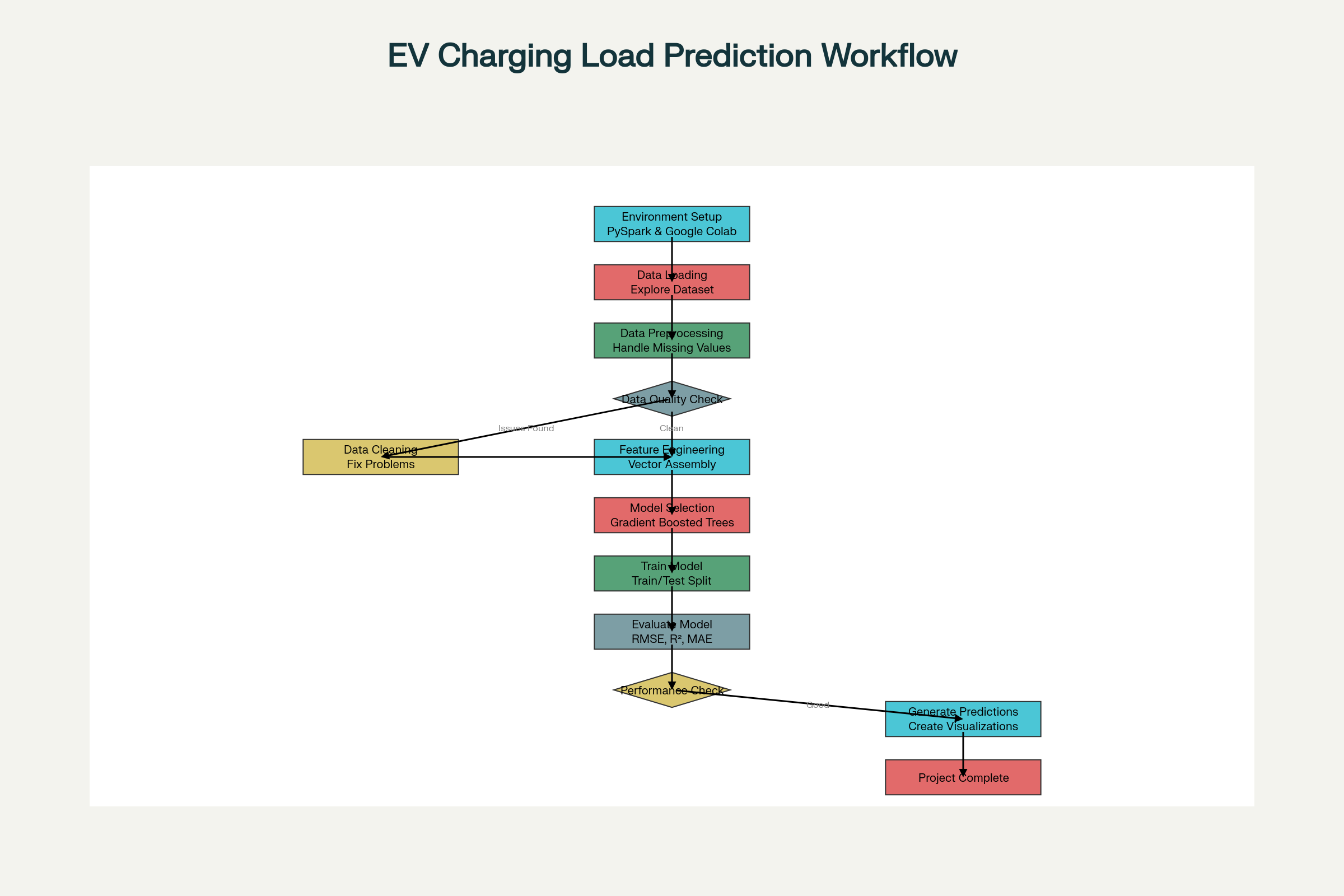
**Future Enhancements**

* Incorporate time-based features (hour, day, holidays), and real EV charging load data, replacing the housing dataset.
* Add weather, traffic, and electricity pricing data for richer feature spaces.
* Experiment with deep learning models (LSTM, Transformers) for improved temporal modeling.
* Deploy real-time prediction using Spark Streaming and Kafka.
* Use advanced visualization (Dashboards, Plotly) and integrate with grid management systems.
* Implement model retraining and drift detection for long-term reliability.

**References** available in the original PDF. For a version with live links and all references, refer to the PDF document:

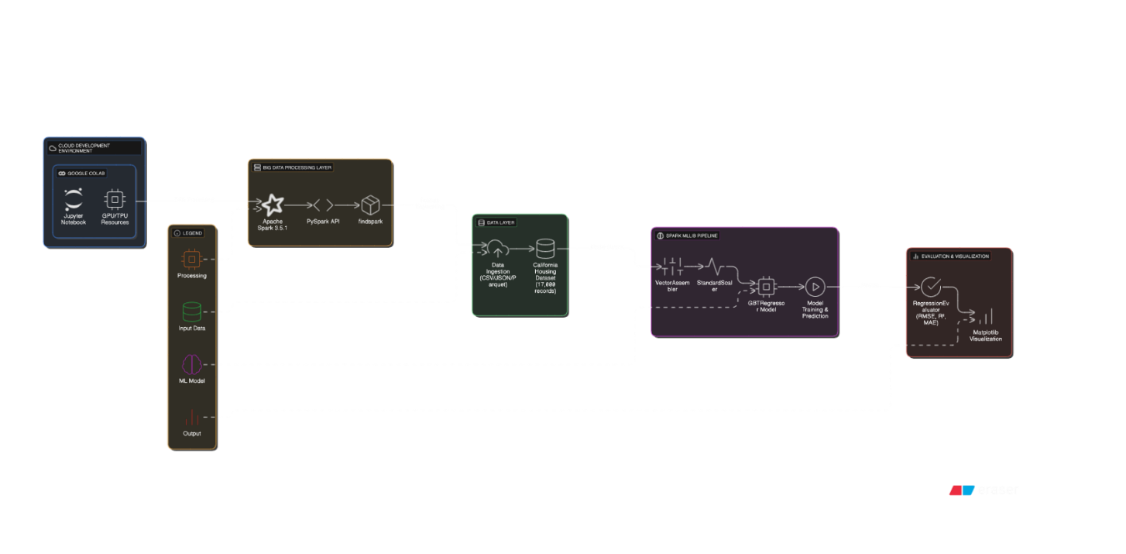
[EV\_Charging\_Load\_Prediction\_Project\_Documentation.pdf]

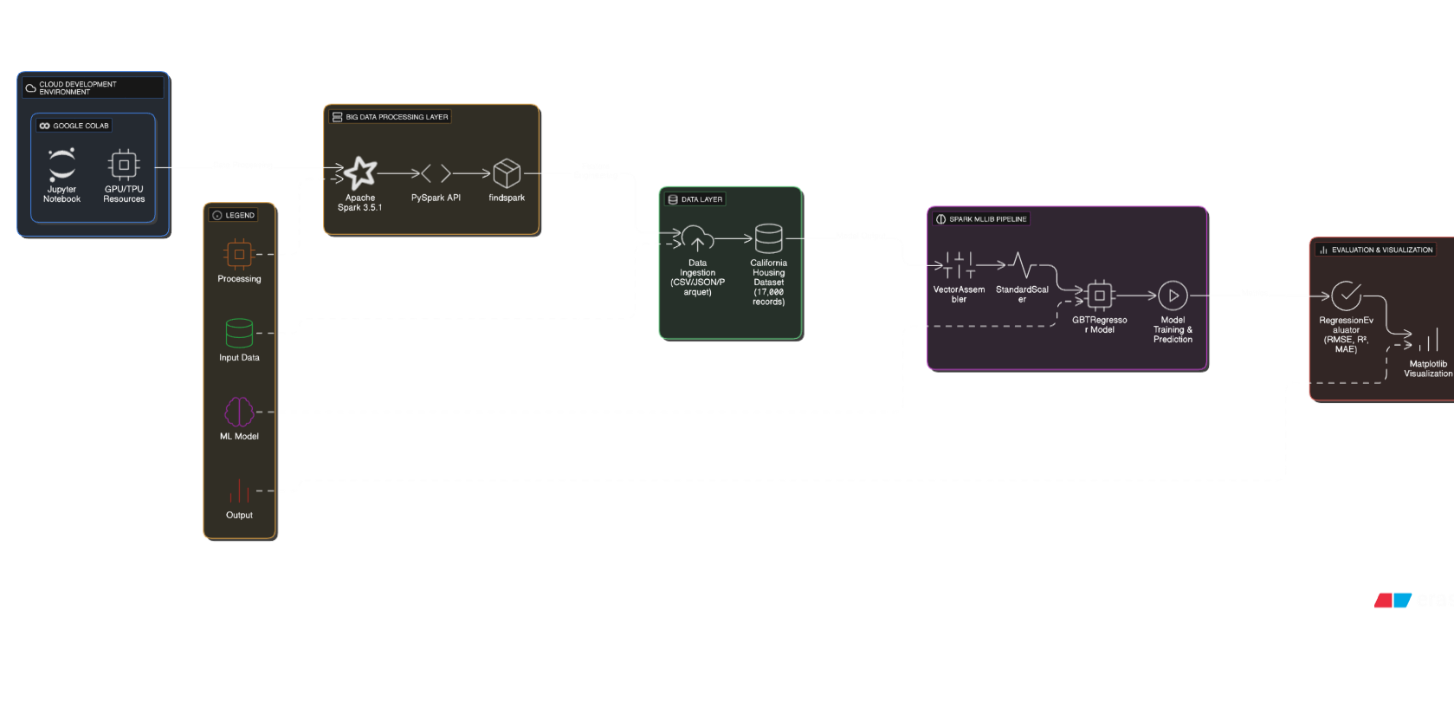
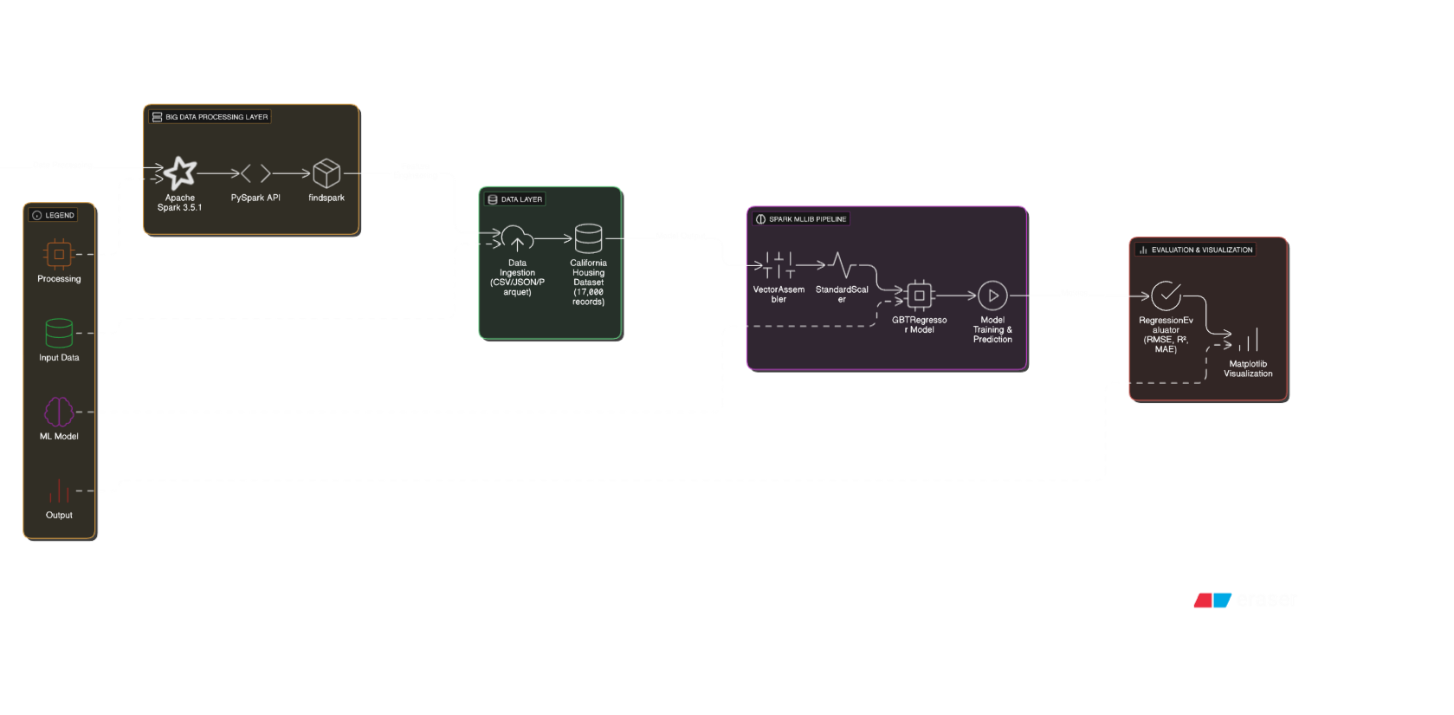
[System workflow diagram]



EV Charging Station Load Prediction Project Workflow

Architecture diagram





System Architecture for EV Charging Load Prediction

Let me know if you want a downloadable .docx file or require any adjustments!

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1. <https://www.nature.com/articles/s41598-025-13180-3>

1. <https://www.sciencedirect.com/science/article/pii/S0306261916311667>

1. <https://github.com/shubanborkar/EV-Charge-Demand>

1. <https://www.sciencedirect.com/science/article/pii/S2352467725000396>

1. <https://www.sciencedirect.com/science/article/abs/pii/S0960148125018051>