BIRMINGHAM CITY University

Project Title: Used car Price Prediction System

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Abstract- This report explains how a system was built to predict used car prices accurately. The project started by studying data from a real-world Used Car Prices dataset on Kaggle. The data was handled by a strong MLOPs pipeline that had been created, which included storing it in a database, checking data quality, cleaning and preparing it, and building a prediction model using XGBoos with optuna hyperparameter tuningt. Tools like Apache Airflow, Docker, Redis, and MLflow helped manage the workflow and track experiments. FastAPI made the final model available through an API. The report also looks at important legal and ethical issues like privacy and fairness. In the end, the model delivered a working price prediction system and a clear process showing good practices in managing data and machine learning.

Introduction and Background

Predicting the price of a used car is a common problem faced by many buyers and sellers. The used car market is vast and dynamic with several factors like brand, model year, mileage, fuel type, and accident history which determine prices. Determining a fair price manually often leads to inconsistent evaluation, underpricing and overpricing (Arora & Garg, 2020). Hence data and machine learning are used to make this process more accurate and easier.

In recent years, Machine Learning has become increasingly important in automotive industry for pricing and recommendation (Sharma et al., 2021). According to Ahmed et al. (2019), machine learning model works better than traditional pricing methods because they can find complex patterns in data that people might miss. Models like Regression, Random Forest and XG boost have been accurate at predicting car prices using processed data.

Problem Identification

This project's main goal is to build a predictive regression model to estimate car prices based on these features. This is a problem where the target variable is the car's price including real-world listings with both numerical and categorical attributes (TaeeefNajib, 2022). Similar approaches in the past have used machine learning models such as Random Forest and XGBoost with good results (Yadav and Shukla, 2021). This project not only helps in learning about ml but also shows how it can solve real-life problems in the automotive and marketing industries.

Source Data Analysis and Selection

Dataset 1: *Utah Real Estate Data*

This Dataset represents 4440 property listings from Utah with 14 columns, collected from Realtor.com using Apify's API as obtained via Kaggle where I found this dataset. While the originally meant for property sales created for education and analytical use.

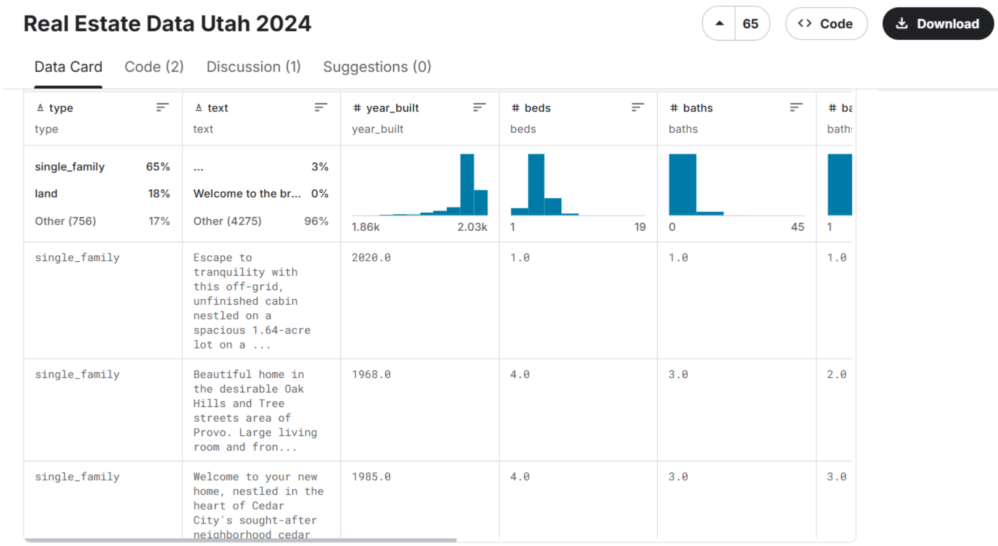


Fig 1. Dataset 1

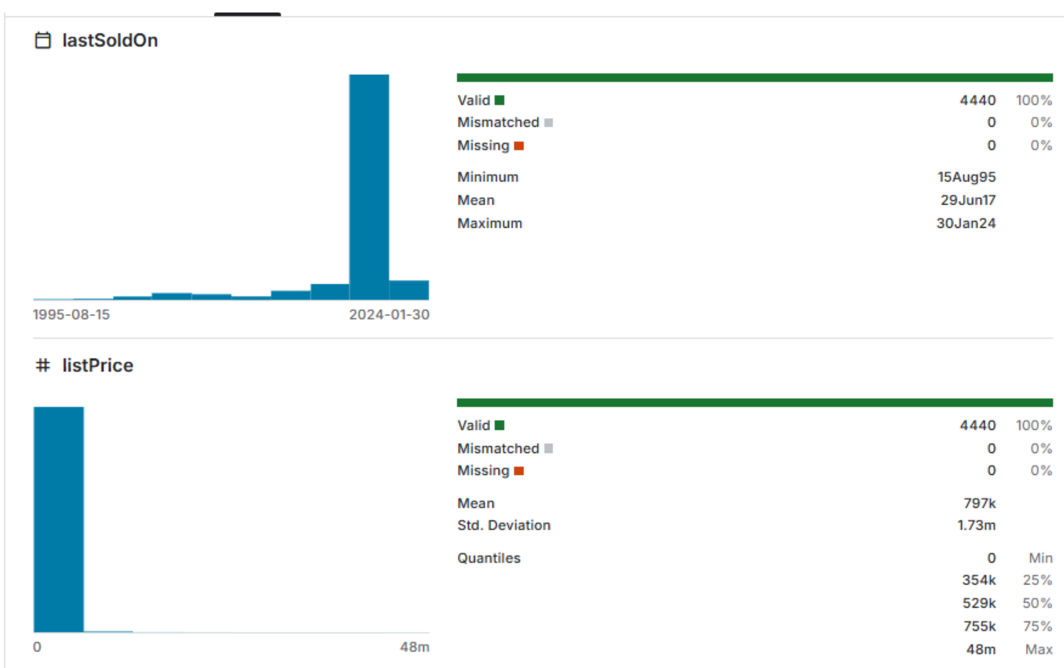


Fig 2. Dataset target variable description

It's structure is simple table flat file, currently stored as downloadable file in CSV format residing physically on system file once downloaded.

Feature	**Feature Description**	**Data Type**
type	Type of property (single-family,land)	String
text	Description of property	String

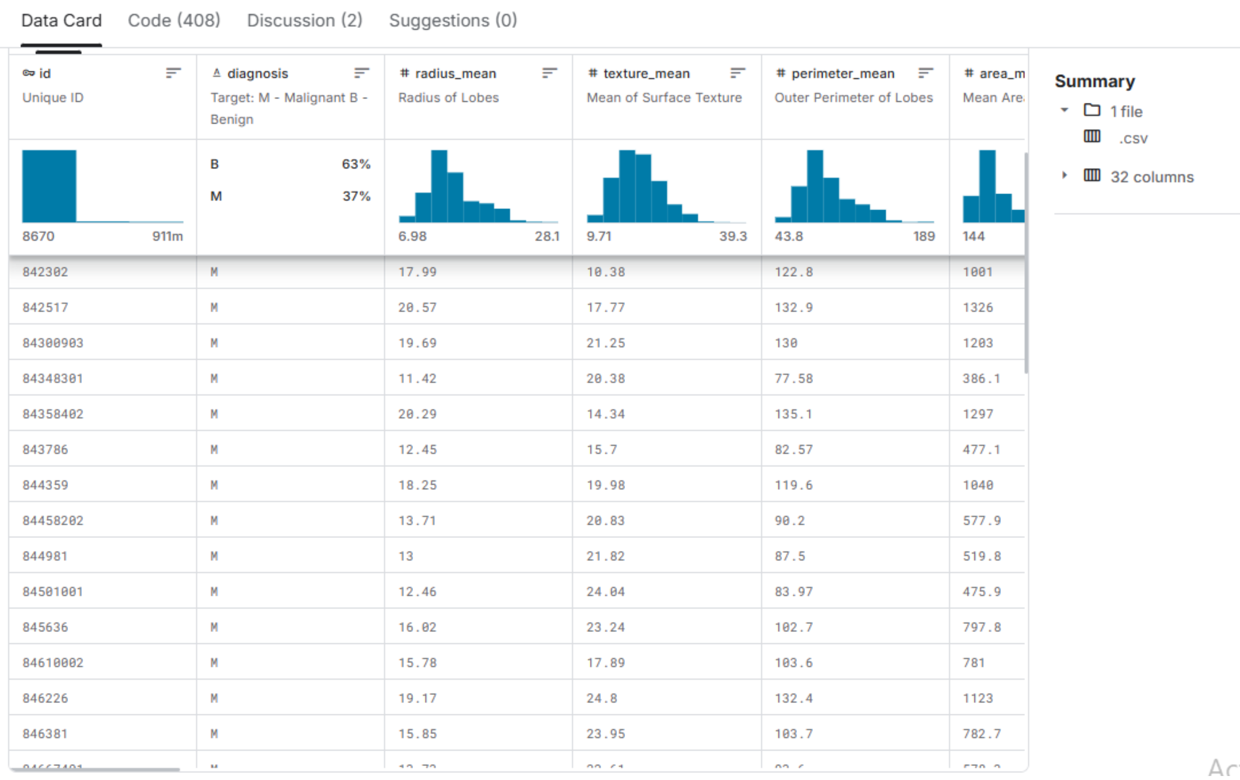
Year_built	Year the property was built	Integer
beds	Number of bedrooms	Integer
baths	Number of bathrooms	Integer
baths_full	Number of Full bathrooms	Integer
Baths_half	Number of Half bathrooms	Integer
garage	Number of garage sizes	Integer
lot_sqft	Lot size in square feet	Integer
sqft	Property size in square feet	Integer
stories	Number of stories	Integer
lastSoldOn	Date the property was last sold on	Date / String (#####)
listPrice	Listing price of the property	Integer
status	Current status of the property	

Table 1: Feature Description Table of Utah Real State

This dataset is suitable for developing supervised ml models for regression task listPrice column as a target variable remaining as predictor variables . The ListPrice values act as “Ground Truth”reflecting seller listed price from realtor.com. The dataset is clean, has no missing values.

Dataset 2: *Breast Cancer Prediction*

This dataset consists of 569 records with 32 features that describes cell nuclei, originated from the university of Wisconsin hospitals from actual patient to support breast cancer diagnosis by classifying breast tumors as cancerous or not based on cell features. Originally in UCI repository but I obtained this from kaggle.



id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_m
842302	M	17.99	10.38	122.8	1001
842517	M	20.57	17.77	132.9	1326
84300903	M	19.69	21.25	130	1203
84348301	M	11.42	20.38	77.58	386.1
84358402	M	20.29	14.34	135.1	1297
843786	M	12.45	15.7	82.57	477.1
844359	M	18.25	19.98	119.6	1040
84458202	M	13.71	20.83	90.2	577.9
844981	M	13	21.82	87.5	519.8
84501001	M	12.46	24.04	83.97	475.9
845636	M	16.02	23.24	102.7	797.8
84610002	M	15.78	17.89	103.6	781
846226	M	19.17	24.8	132.4	1123
846381	M	15.85	23.95	103.7	782.7

Fig 3. Dataset 2

The dataset structured ada flat CSV file, each row represents a sample and 32 columns as cell features, available for download from kaggle / UCI Repository.

Feature	Feature Description	Data Type
ID	Unique identifier number for each sample.	Integer
Diagnosis	The target variable; indicates if the tumor is Malignant (M) or Benign (B) .	String
Radius_mean	Average distance from the center to points on the perimeter of the cell nuclei.	Integer
Texture_mean	Average of the standard deviation of gray-scale values in the cell nuclei.	Integer
Perimeter_mean	Average perimeter of the cell nuclei.	Integer
Area_mean	Average area of the cell nuclei.	Integer
Smoothness_mean	Average of the local variation in radius lengths of the cell nuclei.	Integer
Compactness_mean	Average compactness (perimeter^2 / area - 1.0) of the cell nuclei.	Integer
Concavity_mean	Average severity of concave portions of the contour of the cell nuclei.	Integer
Concave Points_mean	Average number of concave portions of the contour of the cell nuclei.	Integer

Symmetry_mean	Average symmetry of the cell nuclei.	Integer
Fractal_dimension_mean	Average "coastline approximation" fractal dimension of the cell nuclei.	Integer
Radius_se	Standard error of the radius measurement.	Integer
Texture_se	Standard error of the texture measurement.	Integer
Perimeter_se	Standard error of the perimeter measurement.	Integer
Area_se	Standard error of the area measurement.	Integer
Smoothness_se	Standard error of the smoothness measurement.	Integer
Compactness_se	Standard error of the compactness measurement.	Integer
Concavity_se	Standard error of the concavity measurement	Inteer
Concave points_se	Standard error of the concave points measurement.	Integer
Symmetry_se	Standard error of the symmetry measurement.	Integer
Fractual_dimension_se	Standard error of the fractal dimension measurement.	Integer
Radius_worst	Mean of the three largest radius values found in the image.	Integer
Texture_worst	Mean of the three largest texture values found in the image	Integer
Perimeter_worst	Mean of the three largest perimeter values found in the image.	Integer
Area_worst	Mean of the three largest area values found in the image.	Integer
Smoothness_worst	Mean of the three largest smoothness values found in the image.	Integer
Compactness_worst	Mean of the three largest compactness values found in the image.	Integer
Concavity_worst	Mean of the three largest concavity values found in the image.	Integer
Concave points_worst	Mean of the three largest concave points values found in the image.	Integer
Symmetry_worst	Mean of the three largest symmetry values found in the image.	Integer
Fractual_dimesnsion_worst	Mean of the three largest fractal dimension values found in the image.	Integer

Table 2: Feature Description Table of Breast Cancer

This dataset is ideal for binary classification task, with target variable is diagnosis (Maligant = M) & (Benign = B) . The "Ground Truth" as classification of the tumor is verified through medical diagnosis & biopsy results in university. Though it contains only 569 rows & no missing values, it is commonly used in ML projects for cancer classification tasks, providing real-life problem.

Dataset 3: *Used Car Prices*

This dataset represents information about used cars, collected from the automotive marketplace website cars.com , with various attributes to predict the price of used vehicles. It was scraped and compiled by the creator, making it available on Kaggle for analysis, research & for buyers to make informed decisions. The dataset was chosen from Kaggle itself.

This dataset stored as a single table flat file within CSV file named used_cars.csv. Each row represents the car and columns represents features, currently stored as downloadable CSV fileswhich resides physically on the user's local system.

Features	Feature Description
ID	Unique identifier for each car listing in the dataset.
Brand	The manufacturer of the car (e.g., Toyota, Ford, BMW).
Model	The specific model name of the car within the brand (e.g.,M4 Base, F-150, A8 L 55).
Model_year	The designated model year of the vehicle (e.g., 2018, 2020).
Milage	The total distance the car has been driven.
Fuel_type	The type of fuel the car's engine uses (e.g., Gasoline, Diesel, Electric, Hybrid).
Engine	Engine specifications, often including horsepower (HP) and sometimes other details like displacement or codes (e.g., 172.0HP 1., 2.7L V6 24).
Transmission	Type of transmission, often indicating Automatic (A/T) and number of speeds (e.g., A/T, 7-Speed A, 10-Speed).
Ext_col	The exterior color of the vehicle.
Int_col	The interior color of the vehicle.
Accident	Indicator of whether the car has a reported accident history .
Clean_title	Indicator of whether the car possesses a "clean" title, meaning no major negative statuses like salvage, flood damage, etc., are officially recorded .
Price	The target variable; the listing price of the used car in dollar.

Table 3: Feature Description Table of Used car price

This dataset is well suited for supervised regression task price as target variable and 12 other columns as predictors. The listed price serves as the "Ground Truth" though it is not independently verified reflecting real market conditions. Due to its origin from web scraping, it highly contains inconsistencies and missing values presenting realistic challenge in ML tasks.

	0
brand	0
model	0
model_year	0
milage	0
fuel_type	170
engine	0
transmission	0
ext_col	0
int_col	0
accident	113
clean_title	596
price	0

dtype: int64

used_cars	
string	brand
Object	model
int	model_year
Object	milage
Object	fuel_type
Object	engine
Object	transmission
Object	ext_col
Object	int_col
Object	accident
Object	clean_title
Object	price

Fig 4. Dataset Missing values & Data types

	brand	model	model_year	milage	fuel_type	engine	transmission	ext_col	int_col	accident	clean_title	price
0	Ford	Utility Police Interceptor Base	2013	51,000 mi.	E85 Flex Fuel	300.0HP 3.7L V6 Cylinder Engine Flex Fuel Capa...	6-Speed A/T	Black	Black	At least 1 accident or damage reported	Yes	$10,300
1	Hyundai	Palisade SEL	2021	34,742 mi.	Gasoline	3.8L V6 24V GDI DOHC	8-Speed Automatic	Moonlight Cloud	Gray	At least 1 accident or damage reported	Yes	$38,005
2	Lexus	RX 350 RX 350	2022	22,372 mi.	Gasoline	3.5 Liter DOHC	Automatic	Blue	Black	None reported	NaN	$54,598
3	INFINITI	Q50 Hybrid Sport	2015	88,900 mi.	Hybrid	354.0HP 3.5L V6 Cylinder Engine Gas/Electric H...	7-Speed A/T	Black	Black	None reported	Yes	$15,500
4	Audi	Q3 45 S line Premium Plus	2021	9,835 mi.	Gasoline	2.0L I4 16V GDI DOHC Turbo	8-Speed Automatic	Glacier White Metallic	Black	None reported	NaN	$34,999

Fig 5. Dataset 3

5. Dataset Selection and Justification

I chose Used Car Prices dataset for it's realistic and practical applicability in predicting second-hand vehicles and suffiicent size(4009 rows).Compared to Breast Cancer dataset(569 rows, 0 missing values, 30 features) and Utah Real Estate (4440 entries, 0 missing values, 14 features), It aligns better with the used car dataset (12 features, many missing values), making it a practical and ethical choice for end-to-end process of handlin, processing, and modeling imperfect data.

Data Storage Strategy

1. Table Comparison Overview

The star schema was chosen over the snowflake and single big table for my dataset because of it's efficiency and suitability for timeseries data analysis as it helps quickly summarize and analyze trends over time and different factors (like car model, location, or condition), which is important for understanding patterns in used car sales.. From the comparison table below, as u can see snowflake table is a bit more complex than other two and already my dataset has various inconsistencies so to reduce redundancy as well, I chose star schema.

Aspects	Star Schema	One Big Table	Snowflake Schema
Structure	Central fact table with multiple dimension tables (brand, model, year, mileage, etc.)	All data combined in a single large table with all features	Snowflake adds more normalization layers, increasing complexity
Data Redundancy	Low redundancy due to normalization	High redundancy, data duplicated across rows	Snowflake reduces redundancy further but is more complex
Query Performance	Faster for queries that aggregate or filter by dimensions	Faster for machine learning models needing all data in one row	Snowflake slower than star schema due to more joins
Maintenance	Easier to maintain and update dimension tables	Simpler structure but harder to maintain data consistency	Complex maintenance due to multiple layers

Table 4. Logical Schema Comparison Table

2.StarSchema Overview

Below given fig, is my star schema table made in a MariaDB database called usedcar, runs inside a Docker container. This schema has one central fact table and five dimension tables to help remove duplicate data and make storage more efficient as shown in figure.

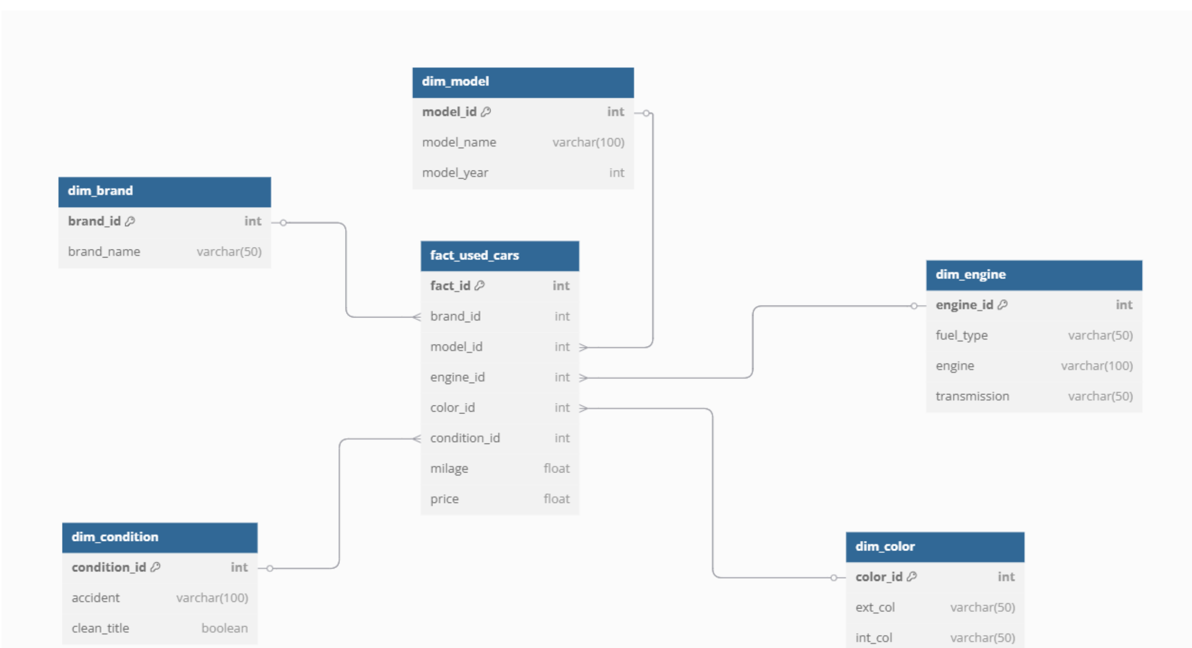


Fig 6: Logical Star Schema diagram

3.ETL Overview

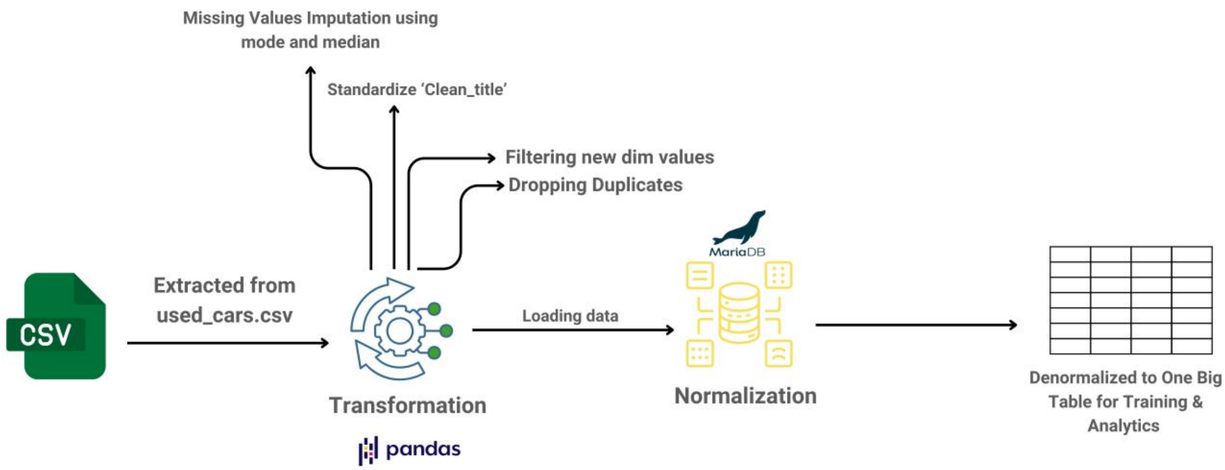


Fig 7. ETL Process

As Shown in the figure.8, ETL process has been adopted. The ETL Process was chosen because the dataset contains multiple inconsistencies from fig,4, among them, duplication, missing values were transformed, standardized clean_title from Yes/NO to 1/0 and enriched so it could fit in star schema table. Still after ETL process, There's more vast issues inside the dataset which are preprocessed in data preprocessing step.

However, since machine learning models work better with flat data, the data are denormalized into one big table after the ETL process.

After preprocessing, the clean data will be saved in Redis, which is a fast in-memory database. This makes it easier to use the data in Great Expectations for validation and during model training. The trained model will also be stored in mlflow so it can be quickly used later for monitoring and predictions.

Final MLOps Pipeline Plan

This section details the data analytics pipeline of Usedcar price predictions. The followings below are procedures for pipelines;

1.Pipeline Overview

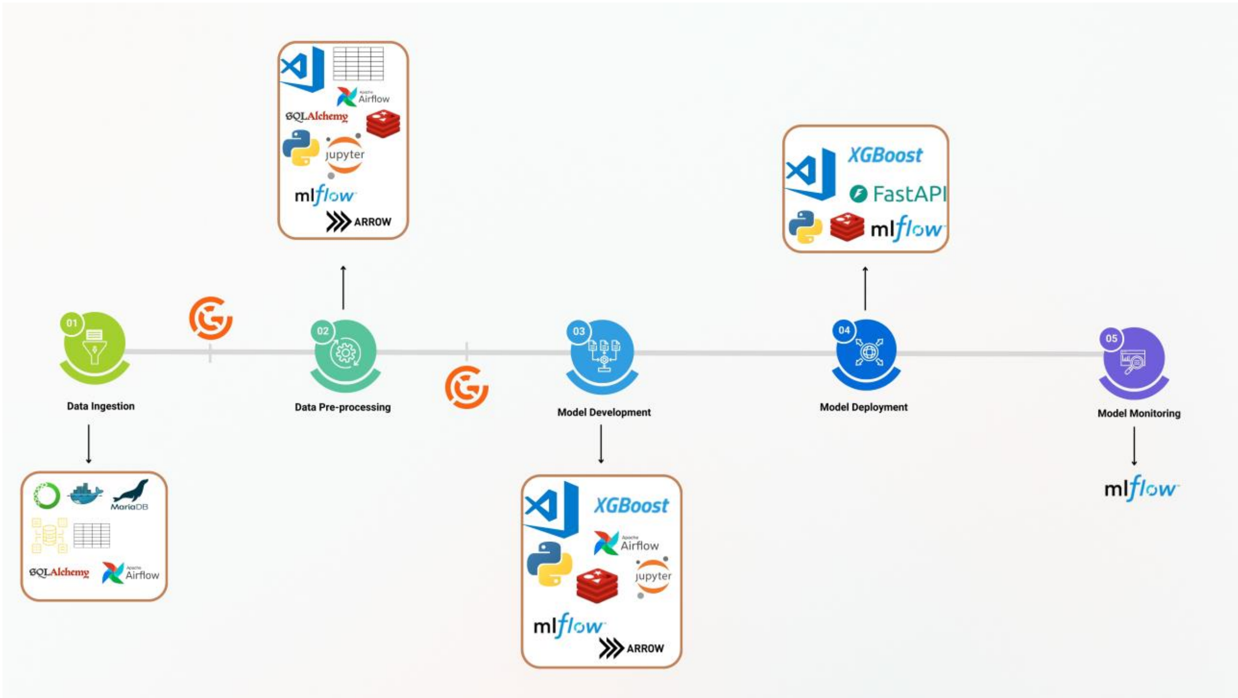


Fig 8. Usedcar Highlevel Pipeline

The pipeline begins with data ingestion from CSV to MariaDB Table, followed by preprocessing and validation using Great Expectations. The preprocessed data is then modeled, monitored and logged for quality assurance, ensuring reliable and consistent data throughout the pipeline.

2. Data Ingestion

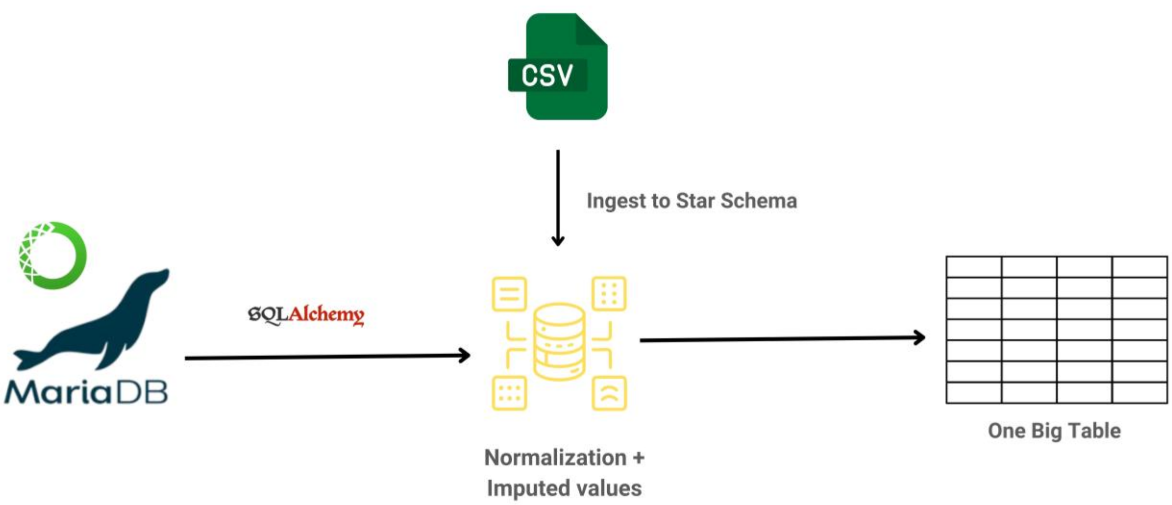


Fig 9.Data Ingestion Process

The used_cars.csv file is loaded into a MariaDB database inside star schema table, normalizing it and again, denormalized to one Big Table ready for validation and preprocessing as shown in figure. Docker along with Anaconda ensure consistent execution of ingestion in controlled environment inside container. Data engineers manage this process for smooth running, while data scientists, analysts, and ML engineers benefit from its outputs for building models. Tools Include : Anaconda, Docker, MariaDB, Python, SQL Alchemy.

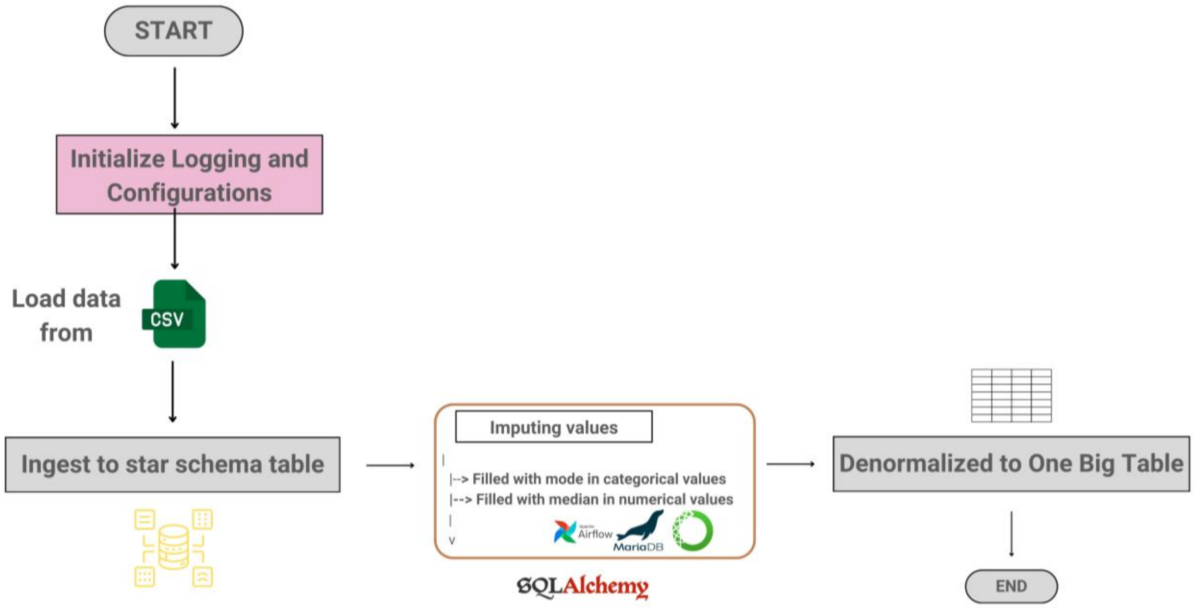


Fig 10. Ingestion Code Execution Process

3. Great Expectation Before

In this step, Great expectation and pandas are used to validate key column to meet the requirement of data quality need for better prediction model like car age should be between 1970-2024, price, brand column has no null values, millages has mi. at the end. This stage is essential to catch data quality issues early, which prevents problems during pre-processing or model training. Data engineers typically handle this step. Tools Include: MariaDB, Pandas, Great Expectations.

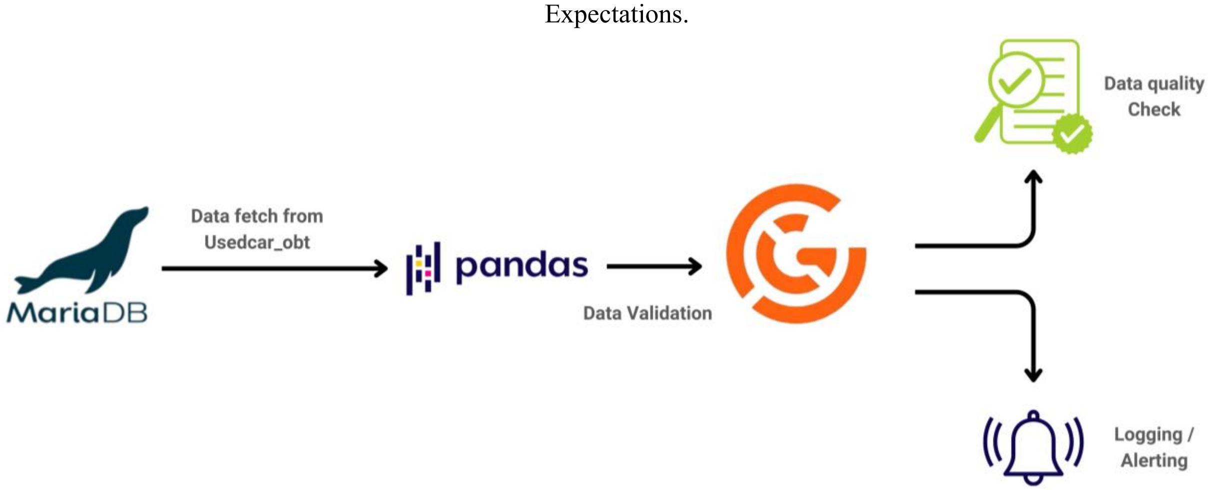


Fig 11. Great Expectation using raw data

4. Data Pre-processing

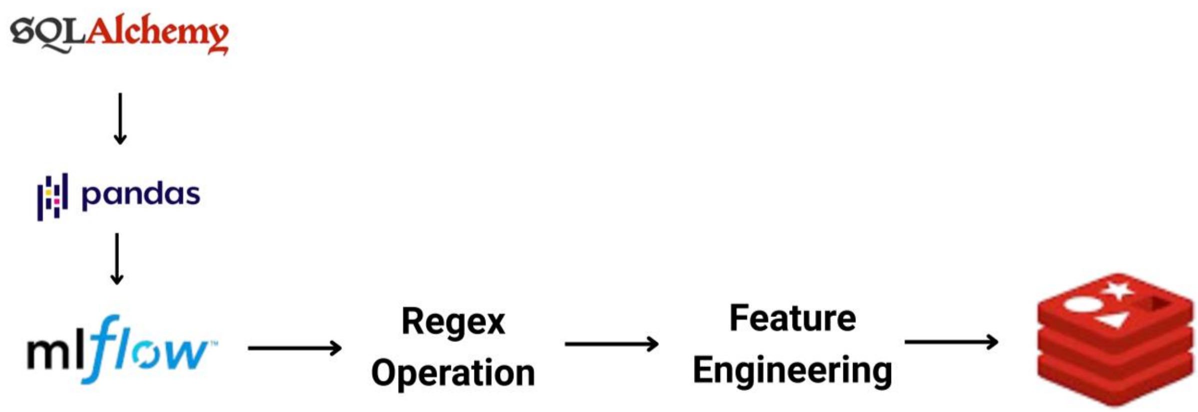


Fig 12. Preprocessing Process

Since missing values are imputed during ETL Process, this process removed incorrect datatypes as everything was in object in fig.4, car_id was removed which served only as an identifier. unwanted characters like mi. , HP, $, brand names were corrected based on associated model names & categorical value are encoded into numerical values. I also standardized the brand, model and colour fields by converting them to lowercase and removing extra characters & Space.

Feature engineering would be involved calculating car's age, advanced parsing was done and colour were grouped to help capture general market preferences. This Step is crucial for better model performance and analysis. The cleaned data is stored in redis in parquet format. Data Scientists designs logic, handle features, and choose cleaning methods; Data Engineers help automate and improve the process. Tools Include: Pandas, Redis, MLflow, SQLAlchemy, Python, Pyarrow,Sklearn.

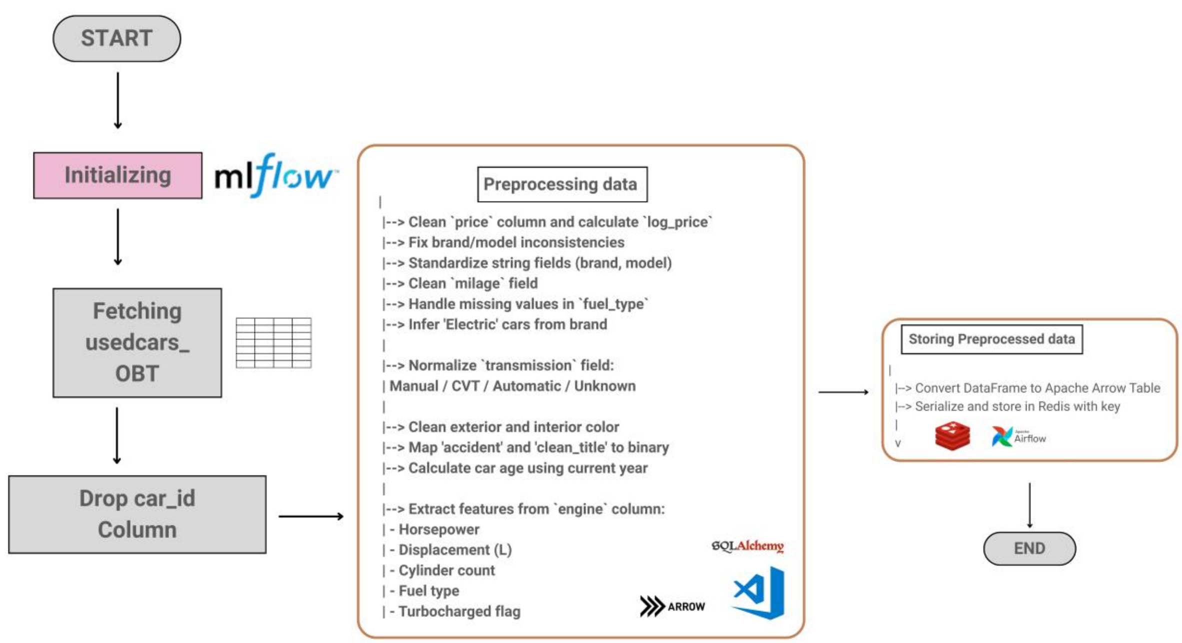


Fig 13.Data Preprocessing Code Process

5. Great Expectation after

This process again performs the validation same way but with processed data stored in redis ensuring data has been cleaned appropriately for improving model performance and feature selection. Data Scientists typically handle this step. Tools Include: Redis , Pandas, Great Expectations.

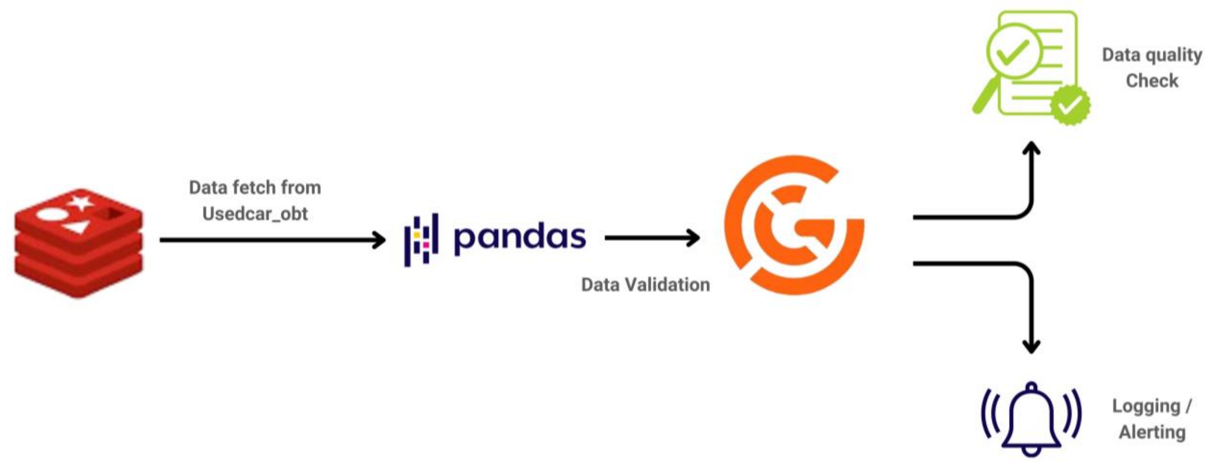


Fig 14. GE after Preprocessing

6. Model Development

Fig 15. Model training process

This stage involves using pre-processed data stored in redis to train, optimize using optuna hyperparameter tuning, evaluate the regression model for predicting car price as shown in fig15/16. The model is retrained and registered in MLflow for future deployment.

Data scientists handle model building, tuning, and explainability, with ML engineers supporting infrastructure and tracking. The deployment team, business stakeholders, and analysts benefit from accurate predictions. Tools Include: Redis, Pyarrow, Sklearn, Python, XGBoost, Mlflow.

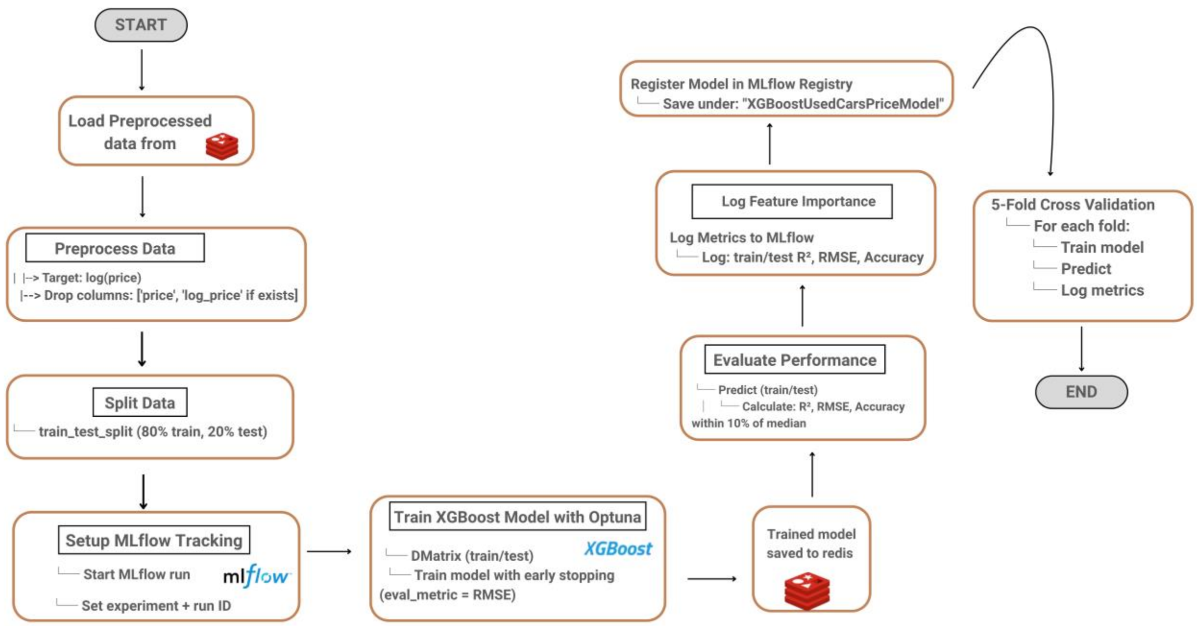


Fig 16.Model development Code Process

7. Model Deployment

Fig 17. Model deployment process

This process takes the model saved in mlflow to operate using Fast API so it can serve as prediction system. The API will be hosted on a server or cloud for users. ML Engineers and DevOps will work together to manage deployment and infrastructure. Tools Include: FastAPI, MLFlow, Python, XGBoost.

8. Model Monitoring

After deployment the model's performance will be monitored and tracked in mlflow to ensure its performance if any changes in data patterns or market trends affect predictions. Monitoring this ensures the model is accurate & responsive, with timely retraining if needed.

Final Pipeline Implementation and Model Deployment

1.Setup and Configuration

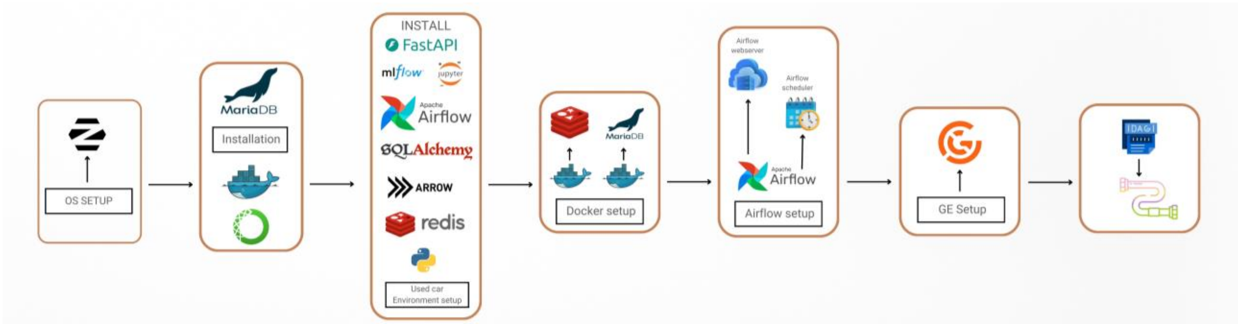


Fig 18.Server Setup

1.1 Linux

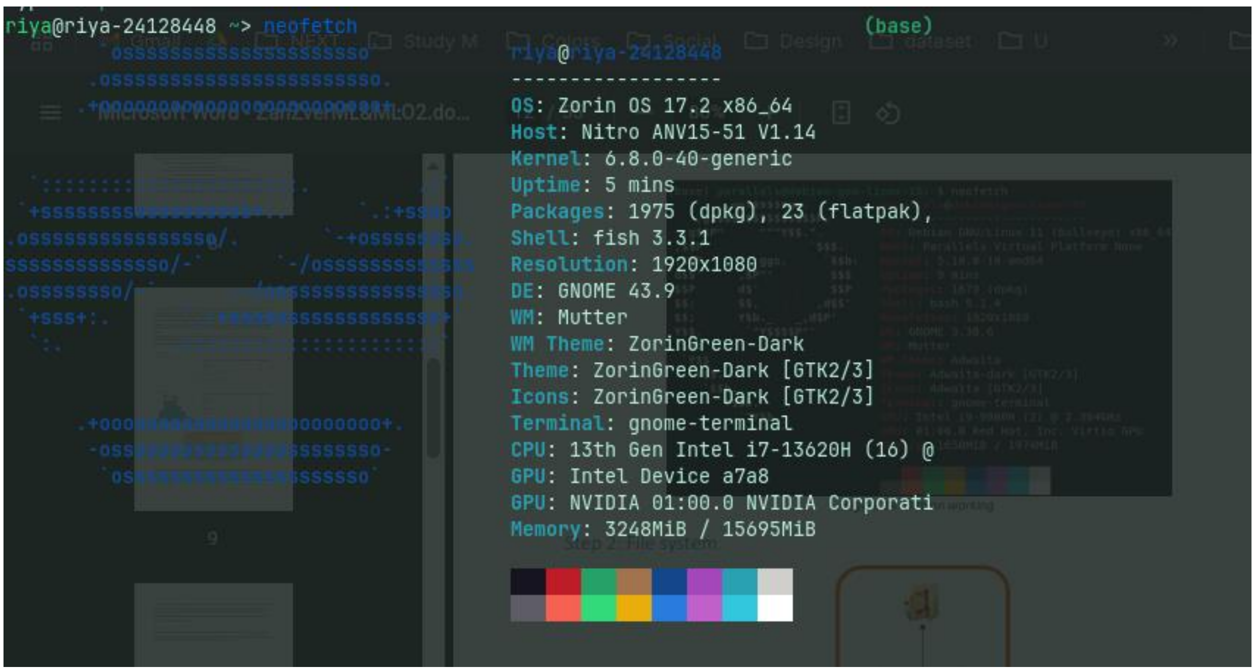


Fig 19.Zorin Setup

1.2 Docker / MariaDB / Anaconda

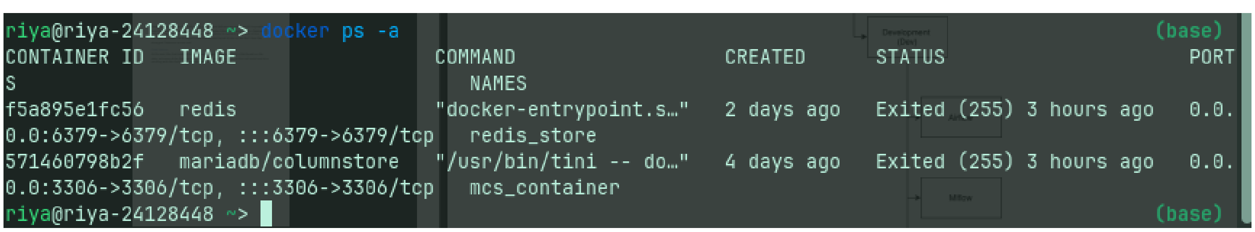


Fig 20.Docker Setup

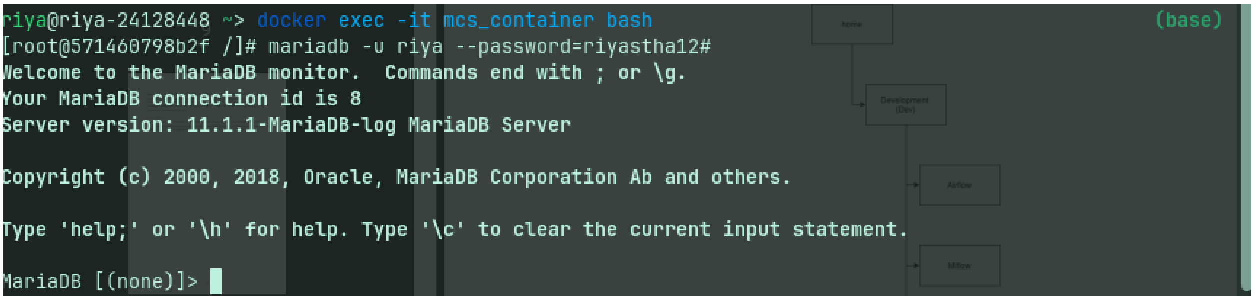


Fig 21.MariaDB Setup

Fig 22. Anaconda Setup

1.3 Environment Setup

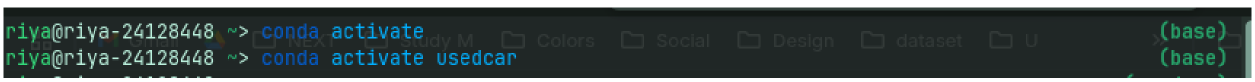


Fig 23.Usedcar environment Setup

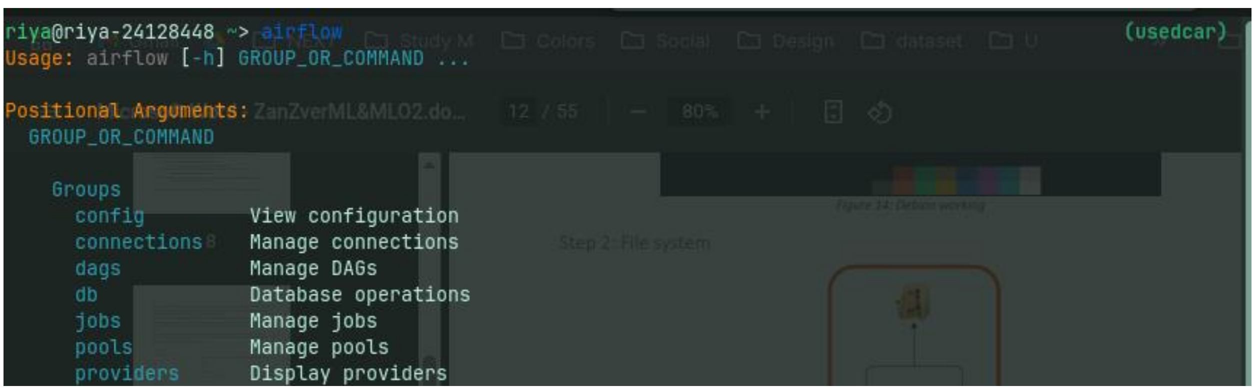


Fig 24.AirflowSetup

Fig 25. Required Tools Setup

1.4 Container Setup

Fig 26. Container Setup

1.5 Airflow Setup

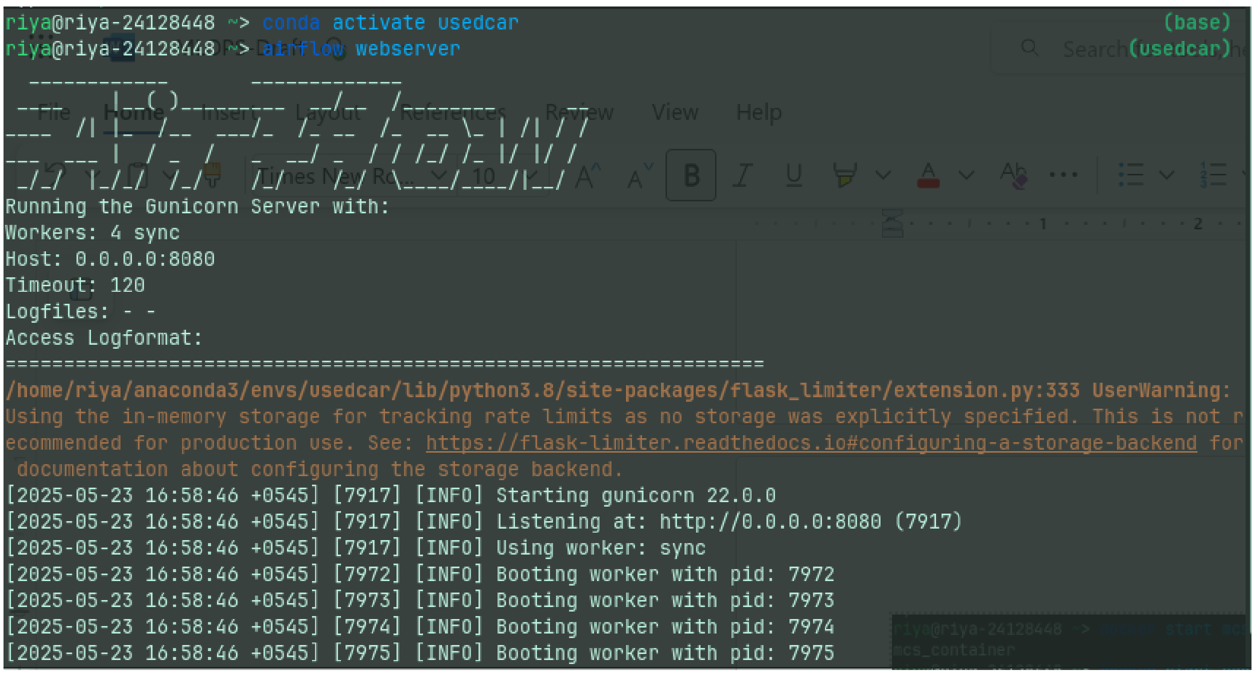


Fig :27 airflow webserver Setup

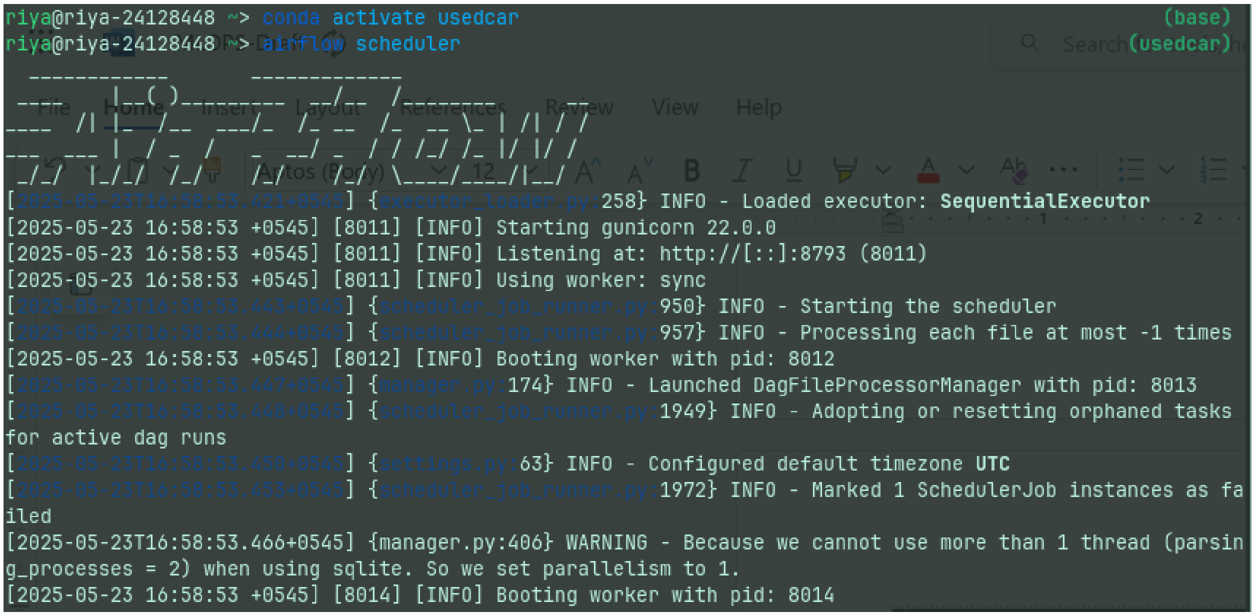


Fig 28: airflow scheduler Setup

1.6 Great Expectations

Fig 29. Great Expectation Setup

1.7 Pipeline Implementation

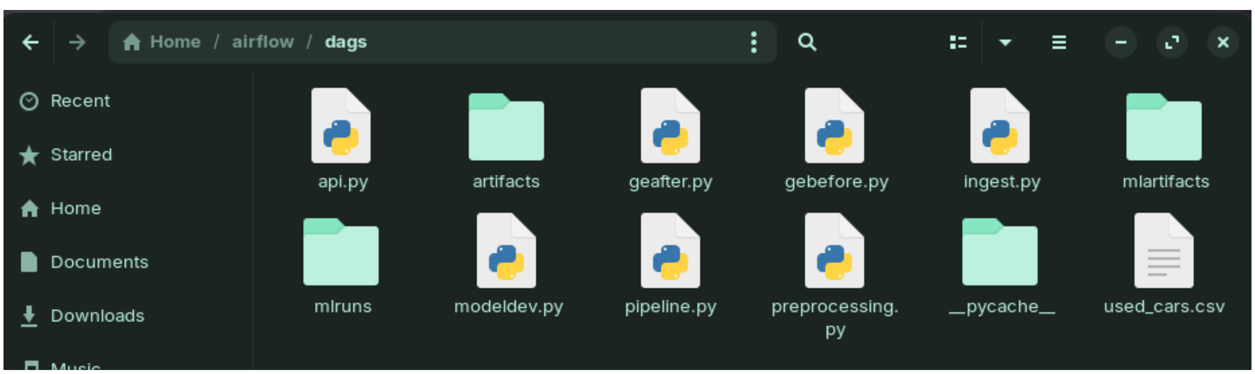


Fig 30: Project file inside dags

```
MariaDB [(none)]> show tables;
ERROR 1046 (3D000): No database selected
MariaDB [(none)]> show databases;
+--------------------+
| Database           |
+--------------------+
| calpontsys         |
| columnstore_info   |
| dbexample1         |
| infinidb_querystats |
| information_schema |
| mysql              |
| performance_schema |
| sys                |
| test               |
| usedcar            |
+--------------------+
10 rows in set (0.005 sec)
```

Fig 31: Usedcar database

```
MariaDB [(none)]> use usedcar
Reading table information for completion of table and column name
You can turn off this feature to get a quicker startup with -A

Database changed
MariaDB [usedcar]> DESCRIBE fact_used_cars;
+--------------+------------+------+-----+---------+-------+
| Field        | Type       | Null | Key | Default | Extra |
+--------------+------------+------+-----+---------+-------+
| car_id       | bigint(20) | YES  |     | NULL    |       |
| model_year   | bigint(20) | YES  |     | NULL    |       |
| milage       | text       | YES  |     | NULL    |       |
| fuel_type    | text       | YES  |     | NULL    |       |
| transmission | text       | YES  |     | NULL    |       |
| price        | text       | YES  |     | NULL    |       |
| brand_id     | bigint(20) | YES  |     | NULL    |       |
| model_id     | bigint(20) | YES  |     | NULL    |       |
| engine_id    | bigint(20) | YES  |     | NULL    |       |
| ext_color_id | bigint(20) | YES  |     | NULL    |       |
| int_color_id | bigint(20) | YES  |     | NULL    |       |
| condition_id | bigint(20) | YES  |     | NULL    |       |
+--------------+------------+------+-----+---------+-------+
12 rows in set (0.001 sec)
```

Fig 32: Usedcars Fact table

```
MariaDB [usedcar]> DESCRIBE dim_brand;
+------------+-------------+------+-----+---------+----------------+
| Field      | Type        | Null | Key | Default | Extra          |
+------------+-------------+------+-----+---------+----------------+
| brand_id   | int(11)     | NO   | PRI | NULL    | auto_increment |
| brand_name | varchar(50) | YES  |     | NULL    |                |
+------------+-------------+------+-----+---------+----------------+
```

Fig 33: Dimension brand Table

```
MariaDB [usedcar]> DESCRIBE dim_engine;
+--------------+--------------+------+-----+---------+----------------+
| Field        | Type         | Null | Key | Default | Extra          |
+--------------+--------------+------+-----+---------+----------------+
| engine_id    | int(11)      | NO   | PRI | NULL    | auto_increment |
| fuel_type    | varchar(50)  | YES  |     | NULL    |                |
| engine       | varchar(100) | YES  |     | NULL    |                |
| transmission | varchar(50)  | YES  |     | NULL    |                |
+--------------+--------------+------+-----+---------+----------------+
4 rows in set (0.001 sec)
```

Fig 34: Dimension engine Table

```
MariaDB [usedcar]> DESCRIBE dim_color;
+----------+-------------+------+-----+---------+----------------+
| Field    | Type        | Null | Key | Default | Extra          |
+----------+-------------+------+-----+---------+----------------+
| color_id | int(11)     | NO   | PRI | NULL    | auto_increment |
| ext_col  | varchar(50) | YES  |     | NULL    |                |
| int_col  | varchar(50) | YES  |     | NULL    |                |
+----------+-------------+------+-----+---------+----------------+
3 rows in set (0.001 sec)
```

Fig 35: Dimension Color Table

```
MariaDB [usedcar]> DESCRIBE dim_condition;
+--------------+--------------+------+-----+---------+----------------+
| Field        | Type         | Null | Key | Default | Extra          |
+--------------+--------------+------+-----+---------+----------------+
| condition_id | int(11)      | NO   | PRI | NULL    | auto_increment |
| accident     | varchar(100) | YES  |     | NULL    |                |
| clean_title  | tinyint(1)   | YES  |     | NULL    |                |
+--------------+--------------+------+-----+---------+----------------+
3 rows in set (0.001 sec)
```

Fig 36: Dimension ConditionTable

```
MariaDB [usedcar]> DESCRIBE dim_model;
+------------+--------------+------+-----+---------+----------------+
| Field      | Type         | Null | Key | Default | Extra          |
+------------+--------------+------+-----+---------+----------------+
| model_id   | int(11)      | NO   | PRI | NULL    | auto_increment |
| model_name | varchar(100) | YES  |     | NULL    |                |
| model_year | int(11)      | YES  |     | NULL    |                |
+------------+--------------+------+-----+---------+----------------+
3 rows in set (0.001 sec)
```

Fig 37: Dimension Model Table

```
MariaDB [usedcar]> DESCRIBE usedcars_obt;
+--------------+------------+------+-----+---------+-------+
| Field        | Type       | Null | Key | Default | Extra |
+--------------+------------+------+-----+---------+-------+
| brand        | text       | YES  |     | NULL    |       |
| model        | text       | YES  |     | NULL    |       |
| model_year   | bigint(20) | YES  |     | NULL    |       |
| milage       | text       | YES  |     | NULL    |       |
| fuel_type    | text       | YES  |     | NULL    |       |
| engine       | text       | YES  |     | NULL    |       |
| transmission | text       | YES  |     | NULL    |       |
| ext_col      | text       | YES  |     | NULL    |       |
| int_col      | text       | YES  |     | NULL    |       |
| accident     | text       | YES  |     | NULL    |       |
| clean_title  | bigint(20) | YES  |     | NULL    |       |
| price        | text       | YES  |     | NULL    |       |
| car_id       | bigint(20) | YES  |     | NULL    |       |
+--------------+------------+------+-----+---------+-------+
13 rows in set (0.001 sec)
```

Fig 38: One big table

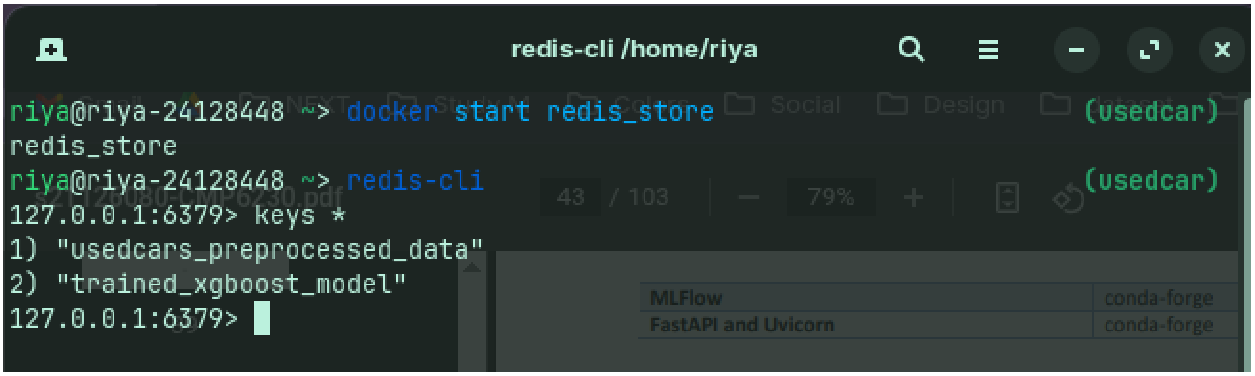


Fig 39: Redis container

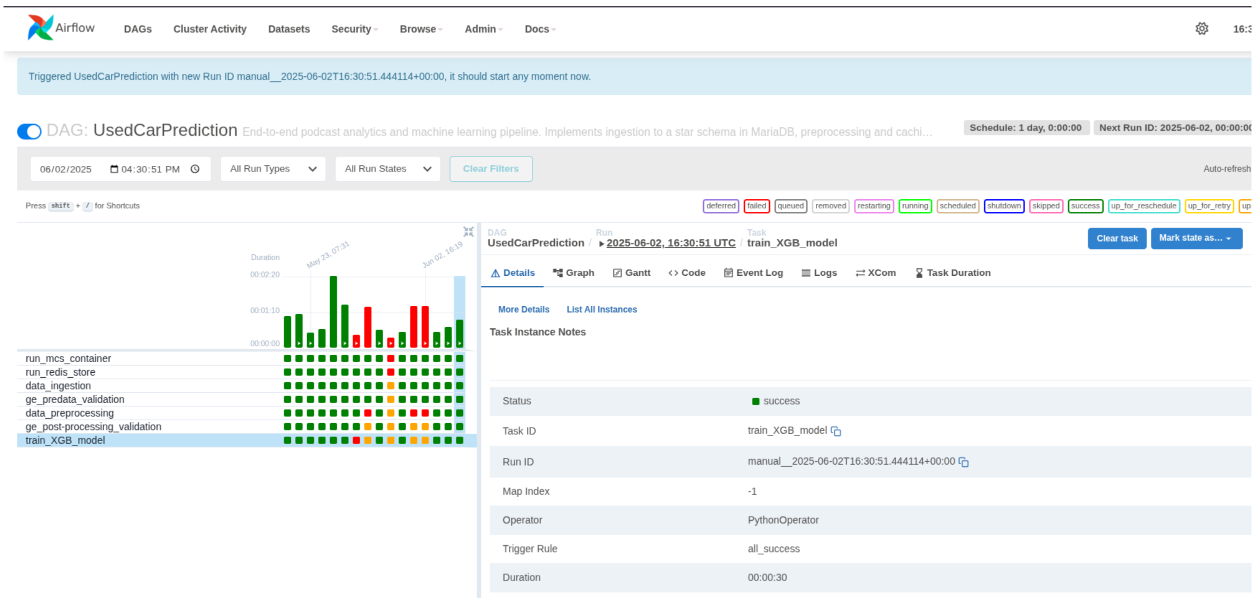


Fig 40:Trained model airflow

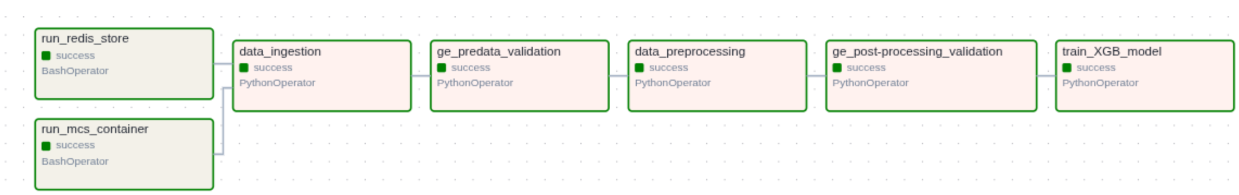


Fig 41: airflow model graph

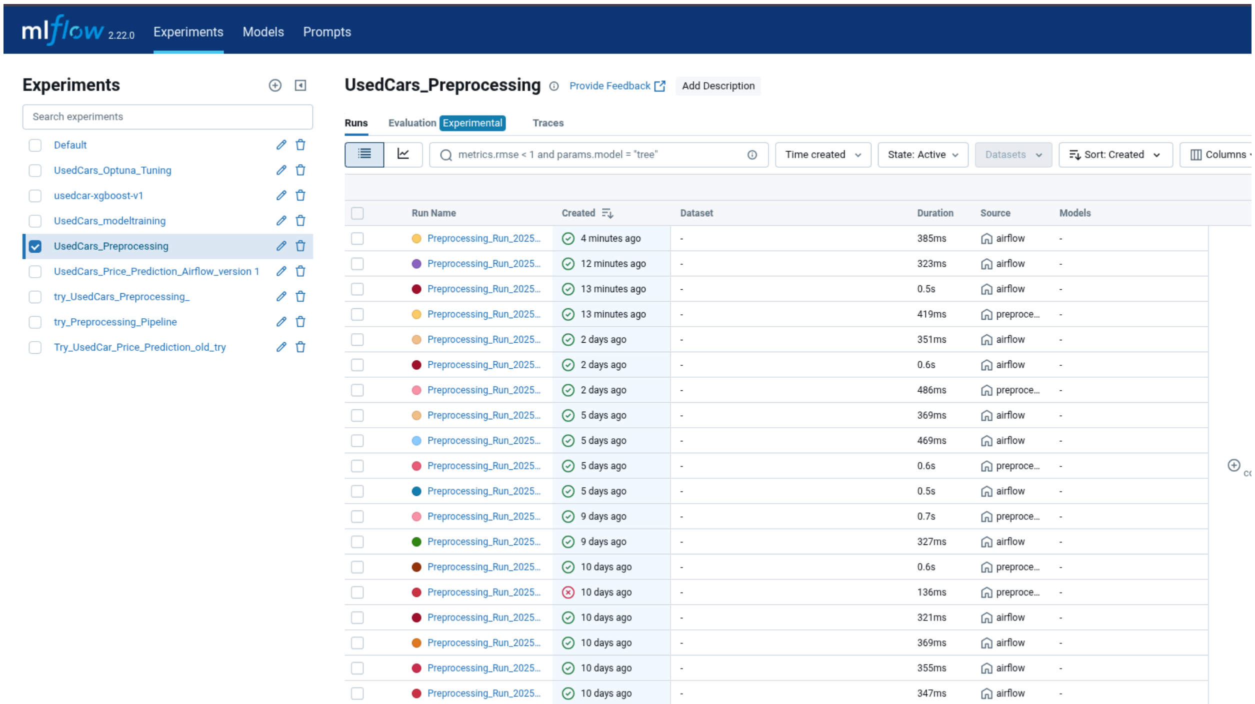


Fig 42: Preprocessing Mlflow

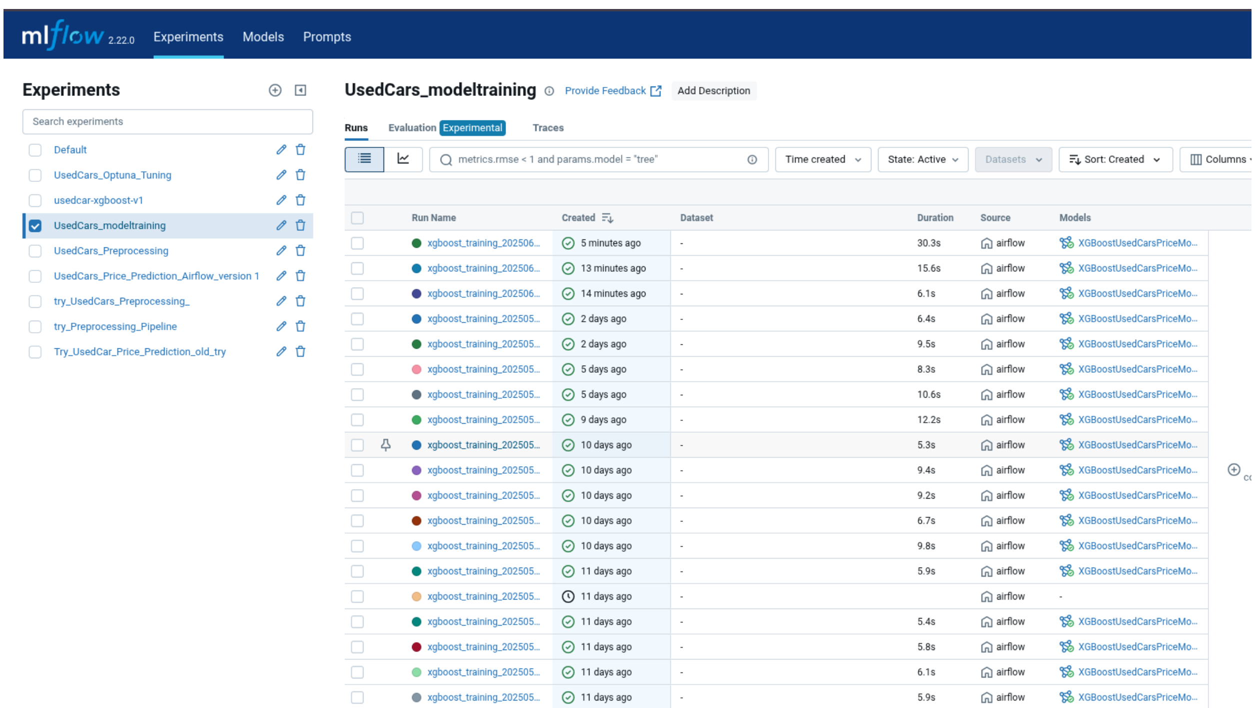


Fig 43: Training model mlflow

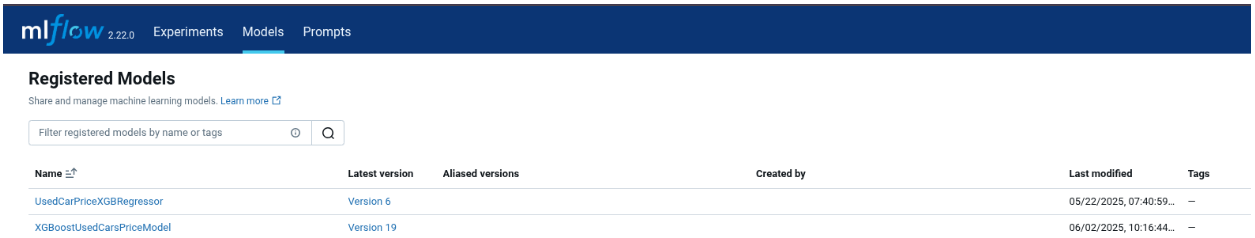


Fig 44: Training model Version

Fig 45: Model predictive value

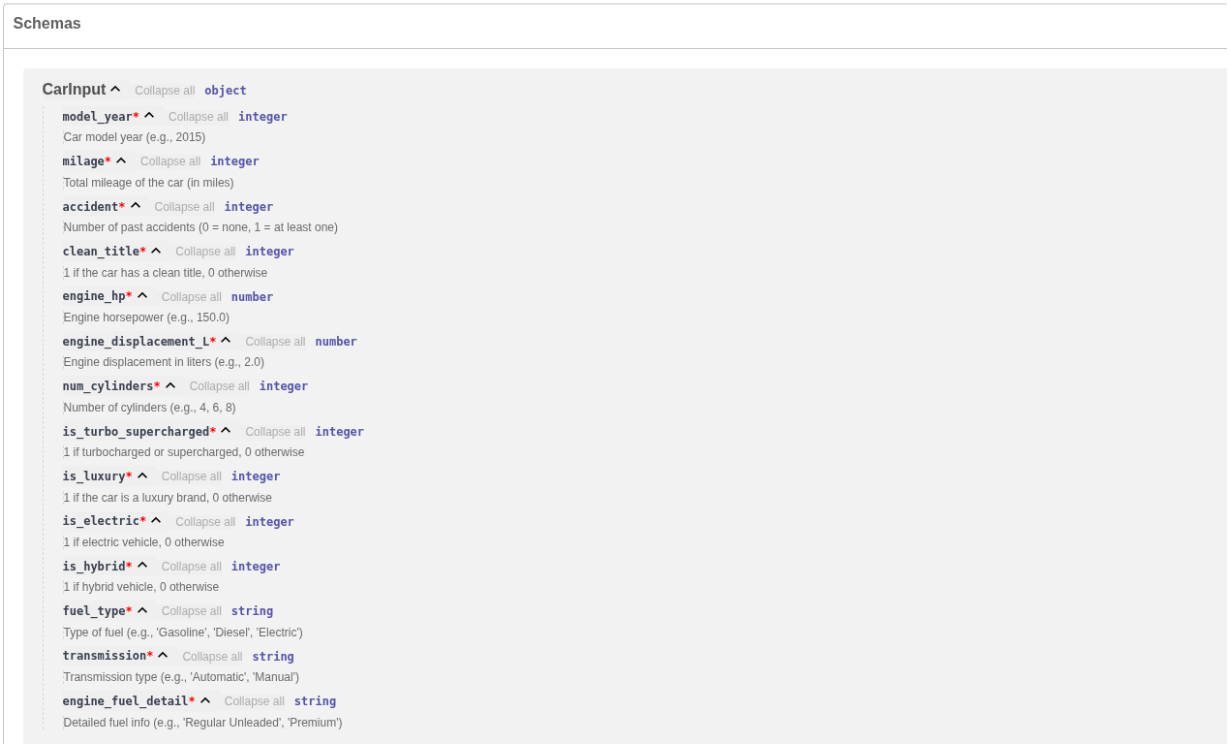


Fig 46: Input Format

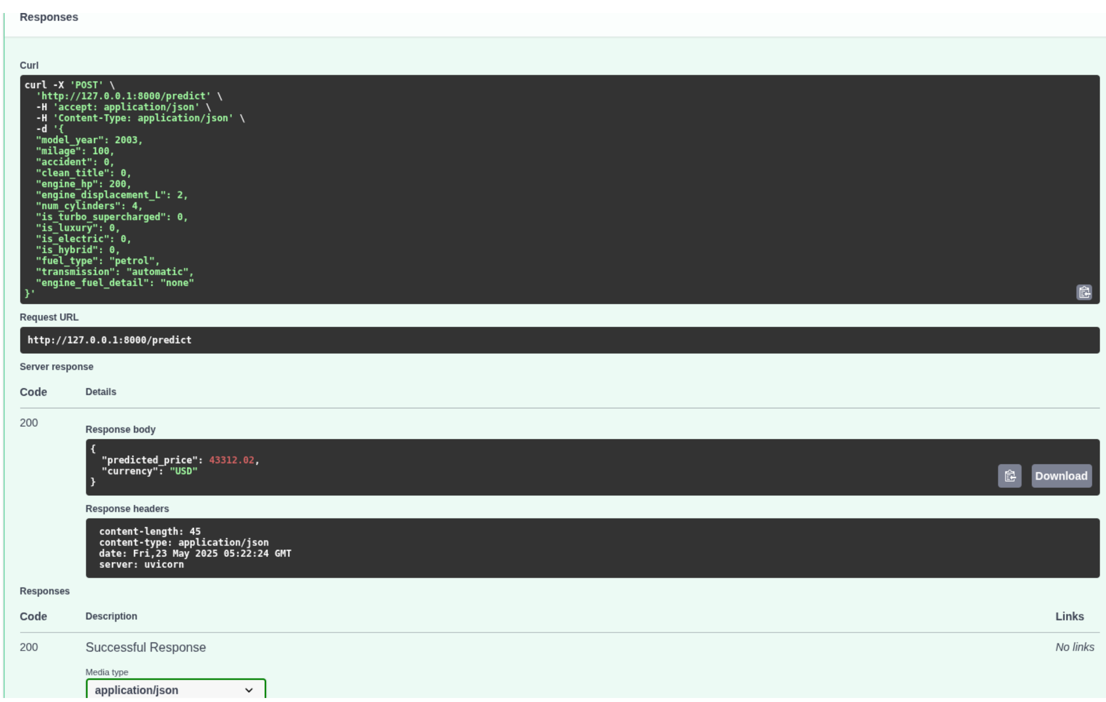


Fig 47: Prediction

Exploratory Data Analysis and Insights

1. comparing raw and preprocessed data differences

1.a) Raw data EDA

Before starting EDA, checking the raw data containing inconsistencies. Here every features datatype is object including price and contains various missing values which where imputed using mode and median. Also it can be seen in this dataset that price as string, contains mixed formatting in columns like engine, transmission and fuel_type, all these are preprocessed in data preprocessing whose result are shown in fig53

5]:

	brand	model	model_year	milage	fuel_type	engine	transmission	ext_col	int_col	accident	clean_title	price
0	Ford	Utility Police Interceptor Base	2013	51,000 mi.	E85 Flex Fuel	300.0HP 3.7L V6 Cylinder Engine Flex Fuel Capa...	6-Speed A/T	Black	Black	At least 1 accident or damage reported	Yes	$10,300
1	Hyundai	Palisade SEL	2021	34,742 mi.	Gasoline	3.8L V6 24V GDI DOHC	8-Speed Automatic	Moonlight Cloud	Gray	At least 1 accident or damage reported	Yes	$38,005
2	Lexus	RX 350 RX 350	2022	22,372 mi.	Gasoline	3.5 Liter DOHC	Automatic	Blue	Black	None reported	NaN	$54,598
3	INFINITI	Q50 Hybrid Sport	2015	88,900 mi.	Hybrid	354.0HP 3.5L V6 Cylinder Engine Gas/Electric H...	7-Speed A/T	Black	Black	None reported	Yes	$15,500
4	Audi	Q3 45 S line Premium Plus	2021	9,835 mi.	Gasoline	2.0L I4 16V GDI DOHC Turbo	8-Speed Automatic	Glacier White Metallic	Black	None reported	NaN	$34,999

Fig 48: raw dataset head

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4009 entries, 0 to 4008
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   brand         4009 non-null   object
 1   model         4009 non-null   object
 2   model_year    4009 non-null   int64
 3   milage        4009 non-null   object
 4   fuel_type     3839 non-null   object
 5   engine        4009 non-null   object
 6   transmission  4009 non-null   object
 7   ext_col       4009 non-null   object
 8   int_col       4009 non-null   object
 9   accident      3896 non-null   object
 10  clean_title   3413 non-null   object
 11  price         4009 non-null   object
dtypes: int64(1), object(11)
memory usage: 376.0+ KB
```

```
Missing Values:
 brand            0
model            0
model_year       0
milage           0
fuel_type      170
engine           0
transmission     0
ext_col          0
int_col          0
accident       113
clean_title    596
price            0
dtype: int64
```

Fig 49: raw datatype and missing values

```python
print_status("Running data quality check...", "STEP")
null_counts_before = df.isna().sum()
total_nulls = null_counts_before.sum()

categorical_cols = ['brand', 'model', 'fuel_type', 'engine', 'transmission',
                    'ext_col', 'int_col', 'accident', 'clean_title']
numerical_cols = ['model_year', 'milage', 'price']

if total_nulls > 0:
    print_status(f"Found {total_nulls} null values across {sum(null_counts_before > 0)} columns:", "WARNING")
    for col, count in null_counts_before[null_counts_before > 0].items():
        print(f"       - {col}: {count} nulls ({count/len(df)*100:.1f}%)")

    print_status("Imputing missing categorical values with mode...", "STEP")
    for col in categorical_cols:
        if col in df.columns and df[col].isna().any():
            mode_value = df[col].mode()[0]
            df[col] = df[col].fillna(mode_value)
            print_status(f"Column '{col}': Filled {null_counts_before[col]} nulls with mode '{mode_value}'", "INFO")

    print_status("Imputing missing numerical values with median...", "STEP")
    for col in numerical_cols:
        if col in df.columns and df[col].isna().any():
            median_value = df[col].median()
            df[col] = df[col].fillna(median_value)
            print_status(f"Column '{col}': Filled {null_counts_before[col]} nulls with median {median_value:.2f}", "INFO")

    null_counts_after = df.isna().sum()
    if null_counts_after.sum() == 0:
        print_status("All null values successfully imputed", "SUCCESS")
    else:
        print_status(f"Warning: {null_counts_after.sum()} null values remain", "WARNING")
else:
    print_status("No null values found in the dataset", "SUCCESS")
```

Fig 50: Imputation code

Since all the datatypes where object, it showed Nan in raw data which where fixed in data ingestion and preprocessing part and the result that data types are changes to integer, Boolean, float are shown in figure:52.

```
[4]: # Missing values
describe = df.describe(include="all")
print("Feature Description:\n", describe)
```

```
Feature Description:
        brand     model   model_year       milage fuel_type  \
count   4009      4009  4009.000000         4009      3839
unique    57      1898          NaN         2818         7
top     Ford  M3 Base           NaN  110,000 mi.  Gasoline
freq     386        30          NaN           16      3309
mean     NaN       NaN  2015.515590          NaN       NaN
std      NaN       NaN     6.104816          NaN       NaN
min      NaN       NaN  1974.000000          NaN       NaN
25%      NaN       NaN  2012.000000          NaN       NaN
50%      NaN       NaN  2017.000000          NaN       NaN
75%      NaN       NaN  2020.000000          NaN       NaN
max      NaN       NaN  2024.000000          NaN       NaN

                             engine transmission ext_col int_col  \
count                          4009         4009    4009    4009
unique                         1146           62     319     156
top     2.0L I4 16V GDI DOHC Turbo          A/T   Black   Black
freq                             52         1037     905    2025
mean                            NaN          NaN     NaN     NaN
std                             NaN          NaN     NaN     NaN
min                             NaN          NaN     NaN     NaN
25%                             NaN          NaN     NaN     NaN
50%                             NaN          NaN     NaN     NaN
75%                             NaN          NaN     NaN     NaN
max                             NaN          NaN     NaN     NaN

             accident clean_title    price
count            3896        3413     4009
unique              2           1     1569
top     None reported         Yes  $15,000
freq             2910        3413       39
mean              NaN         NaN      NaN
std               NaN         NaN      NaN
min               NaN         NaN      NaN
25%               NaN         NaN      NaN
50%               NaN         NaN      NaN
75%               NaN         NaN      NaN
max               NaN         NaN      NaN
```

Fig 51: Feature Description

1.b) Preprocessed data EDA

In this section, the preprocessed data shows how inconsistencies in datatype changes from object to integer, float and Boolean as it can be compared between fig49 and fig52. Also shows descriptive stats on what kind of features were included and converted in fig53

```
def step_1_eda(df):
    print("\n=== Dataset Info ===")
    print(df.info())
    print("\n=== Descriptive Stats ===")
    print(df.describe())

# Run step 1
step_1_eda(df)
```

```
=== Dataset Info ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4009 entries, 0 to 4008
Data columns (total 36 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   model_year                    4009 non-null   int64  
 1   milage                        4009 non-null   float64
 2   accident                      4009 non-null   int64  
 3   clean_title                   4009 non-null   float64
 4   price                         4009 non-null   float64
 5   log_price                     4009 non-null   float64
 6   car_age                       4009 non-null   float64
 7   engine_hp                     4009 non-null   float64
 8   engine_displacement_L         4009 non-null   float64
 9   num_cylinders                 4009 non-null   float64
 10  is_turbo_supercharged         4009 non-null   int64  
 11  milage_per_year               4009 non-null   float64
 12  is_luxury                     4009 non-null   int64  
 13  is_electric                   4009 non-null   int64  
 14  is_hybrid                     4009 non-null   int64  
 15  is_common_color               4009 non-null   int64  
 16  fuel_type_E85 Flex Fuel       4009 non-null   bool   
 17  fuel_type_Electric            4009 non-null   bool   
 18  fuel_type_Gasoline            4009 non-null   bool   
 19  fuel_type_Hybrid              4009 non-null   bool   
 20  fuel_type_Plug-In Hybrid      4009 non-null   bool   
 21  fuel_type_Unknown             4009 non-null   bool   
 22  fuel_type_not supported       4009 non-null   bool   
 23  transmission_CVT              4009 non-null   bool   
 24  transmission_Manual           4009 non-null   bool   
 25  transmission_Unknown          4009 non-null   bool   
 26  engine_fuel_detail_Electric   4009 non-null   bool   
 27  engine_fuel_detail_Flex Fuel  4009 non-null   bool   
 28  engine_fuel_detail_Gasoline   4009 non-null   bool   
 29  engine_fuel_detail_Hybrid     4009 non-null   bool   
 30  engine_fuel_detail_Unknown    4009 non-null   bool   
 31  brand_freq                    4009 non-null   float64
 32  model_freq                    4009 non-null   float64
 33  ext_col_freq                  4009 non-null   float64
 34  int_col_freq                  4009 non-null   float64
 35  brand_model_freq              4009 non-null   float64
dtypes: bool(15), float64(14), int64(7)
memory usage: 716.6 KB
None
```

Fig 52: Preprocessed Feature Datatype

```
=== Descriptive Stats ===
        model_year       milage     accident  clean_title         price  \
count  4009.000000  4009.000000  4009.000000       4009.0  4.009000e+03
mean   2015.515590    -0.006787     0.245947          0.0  4.455319e+04
std       6.104816     0.973526     0.430701          0.0  7.871064e+04
min    1974.000000    -1.225526     0.000000          0.0  2.000000e+03
25%    2012.000000    -0.796969     0.000000          0.0  1.720000e+04
50%    2017.000000    -0.228390     0.000000          0.0  3.100000e+04
75%    2020.000000     0.561913     0.000000          0.0  4.999000e+04
max    2024.000000     3.016068     1.000000          0.0  2.954083e+06

         log_price      car_age    engine_hp  engine_displacement_L  \
count  4009.000000  4009.000000  4009.000000            4009.000000
mean     10.302401    -0.004180    -0.009254              -0.001205
std       0.850058     0.983581     0.954062               0.989581
min       7.601402    -1.226137    -1.785279              -1.614869
25%       9.752723    -0.734661    -0.545033              -0.729761
50%      10.341775    -0.243184    -0.161791              -0.139689
75%      10.819598     0.575943     0.486072               0.671659
max      14.898699     3.020220     3.123145               2.220597

       num_cylinders  ...  milage_per_year    is_luxury  is_electric  \
count    4009.000000  ...      4009.000000  4009.000000  4009.000000
mean       -0.010350  ...        -0.010263     0.380893     0.022449
std         0.953936  ...         0.954692     0.485667     0.148159
min        -1.494604  ...        -1.551534     0.000000     0.000000
25%        -0.134207  ...        -0.723117     0.000000     0.000000
50%        -0.134207  ...        -0.118045     0.000000     0.000000
75%         1.226189  ...         0.559538     1.000000     0.000000
max         2.586586  ...         2.945471     1.000000     1.000000

         is_hybrid  is_common_color   brand_freq   model_freq  ext_col_freq  \
count  4009.000000      4009.000000  4009.000000  4009.000000   4009.000000
mean      0.056872         0.900723     0.047526     0.001120      0.129518
std       0.231627         0.299070     0.031217     0.001196      0.083282
min       0.000000         0.000000     0.000249     0.000249      0.000249
25%       0.000000         1.000000     0.018957     0.000249      0.065104
50%       0.000000         1.000000     0.040659     0.000748      0.123722
75%       0.000000         1.000000     0.078573     0.001247      0.203542
max       1.000000         1.000000     0.096283     0.007483      0.226490

       int_col_freq  brand_model_freq
count   4009.000000       4009.000000
mean       0.293231          0.001119
std        0.218849          0.001196
min        0.000249          0.000249
25%        0.117735          0.000249
50%        0.506111          0.000748
75%        0.506111          0.001247
max        0.506111          0.007483

[8 rows x 21 columns]
```

Fig 53: Preprocessed data head

2. Visualizations on raw and preprocessed Data

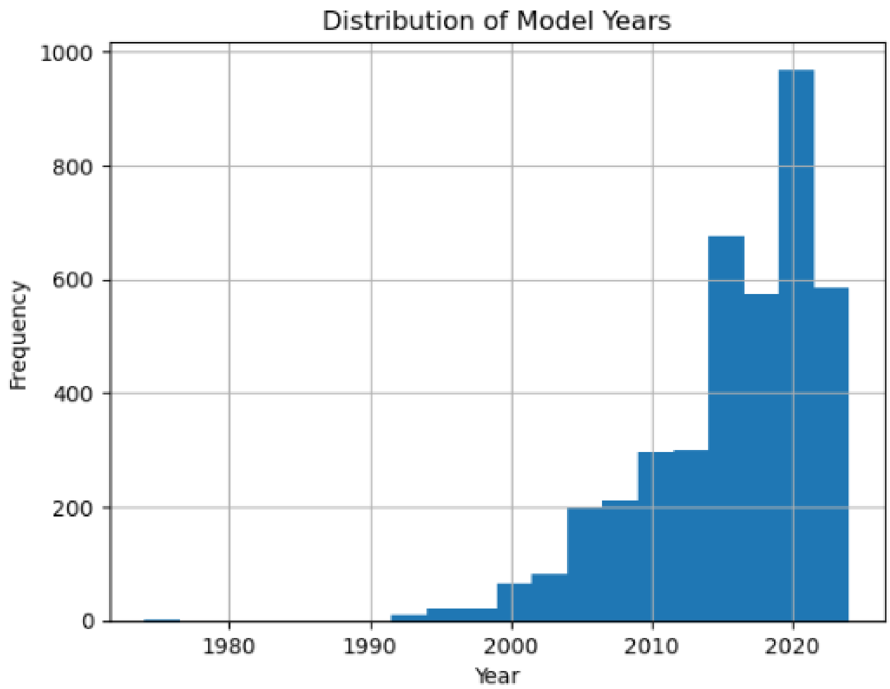


Fig 54: Model Years Distribution

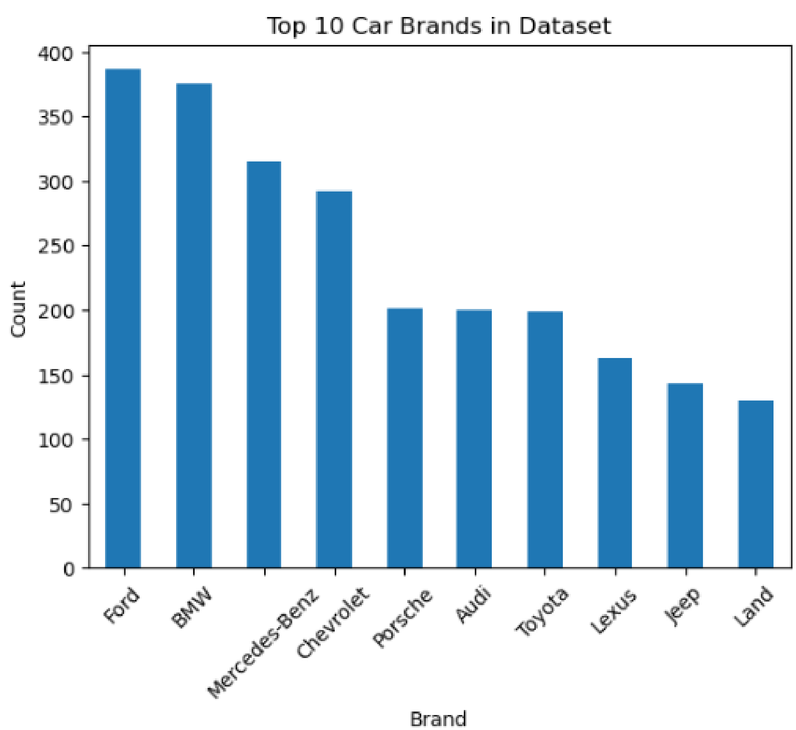


Fig 55: Top 10 Brands

```python
plt.figure(figsize=(12, 8))
corr = df.select_dtypes(include=[np.number]).corr()
sns.heatmap(corr, annot=False, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```

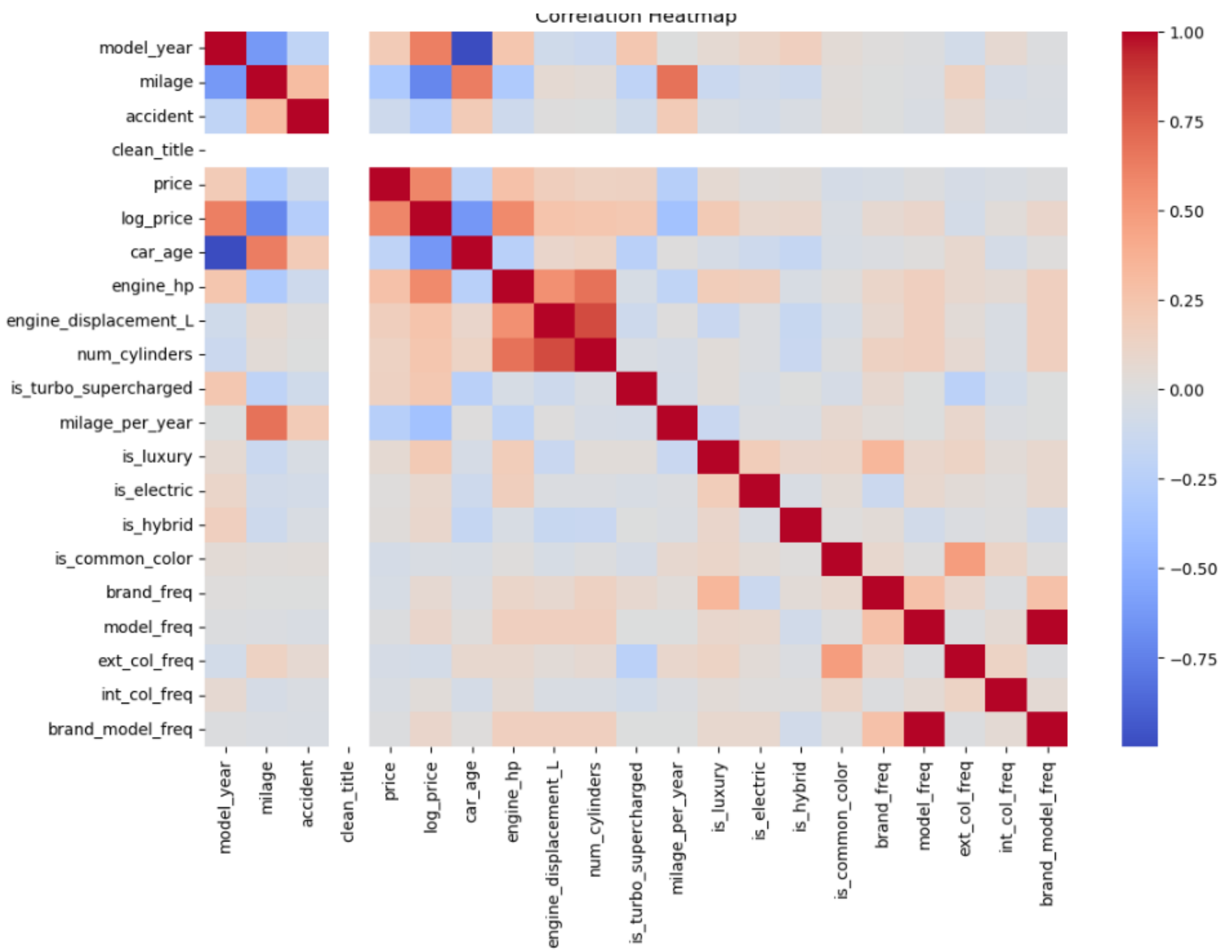


Fig 56: Heatmap

From this correlation heatmap, it shows newest cars tends to have higher price ehile olders are really cheaper. There is strong correlation between engine_hp, engine_displacement_L ans num_cylinders, meaning powerful cars have bigger engines. Price also increases with luxury features and engine power. So the strongest correlation are shown as importnant predictors like, model_year, car_age and engine_hp while int_col_freq, is_common_colour are less useful for this model.

```
=== Top features correlated with log_price ===
log_price                 1.000000
model_year                0.625211
price                     0.594027
engine_hp                 0.573624
engine_displacement_L     0.256221
num_cylinders             0.241404
is_turbo_supercharged     0.220425
is_luxury                 0.210508
brand_model_freq          0.100730
model_freq                0.100466
Name: log_price, dtype: float64
```

Fig 57: Top Feature correlated with log_price

```
=== Outlier Counts by Feature ===
                       Outlier Count
accident                         986
is_common_color                  398
model_freq                       347
brand_model_freq                 347
is_turbo_supercharged            309
price                            244
is_hybrid                        228
engine_hp                        174
is_electric                       90
car_age                           84
milage_per_year                   75
milage                            69
model_year                        67
log_price                         66
```

Fig 58: Outliers in count

```
plt.figure(figsize=(10, 6))
sns.barplot(x=outlier_df.index, y=outlier_df['Outlier Count'], palette='viridis')
plt.xticks(rotation=45, ha='right')
plt.title('Outlier Counts by Feature (IQR Method)')
plt.ylabel('Number of Outliers')
plt.xlabel('Feature')
plt.tight_layout()
plt.show()
```

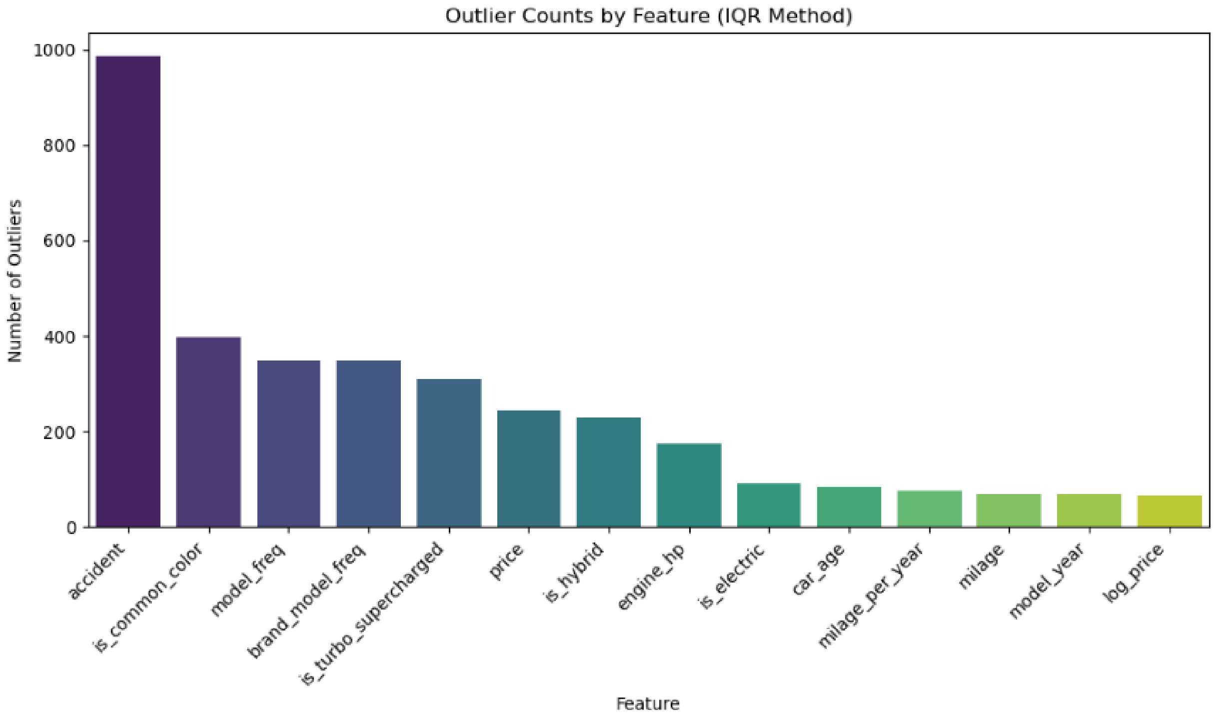


Fig 59: Outliers in Bar Graph

In Outliers of accident, bar graph are high because of imputed value 0 accident occured.

Since the ingested was first passed normalized using star schema and then, denormalized to one big table, all the duplicates were removed and missing values were imputed So, the only difference between initial data source and ingested data has no missing values and duplications.

3. Model Drift

After building and deploying ML model, we must understand model performance might degrade over time. It is because real-world data keeps changing and our model mightn't adapt new patterns and give inaccurate predictions. Since my project uses features like, year, mileage, fuel type, price, transmission which changes overtime, the model will no longer be reliable.

3.a Data Drift

It occurs when the input features changes their distributions overtime For example, Petrol, Diesel will vanish soon so electric will dominate the market so fuel_type = Electric increase. However, my model are mostly trained on petrol diesel cars. Overtime, newer model will enter the market and 1940's vehicles will be very old and 2000s vehicles will start considering old which results in poor predictions as the distribution of year column shifts.

3.b Concept Drift

It occurs when relationship between input features and target variable changes over time. In my case, Mileage might have had a strong negative effect on price, but if buyers begin to focus more on brand or condition rather than mileage, the relationship meaning may change. Even if the data appears similar, it can result in less prediction accuracy.

3.c Drift Handling

To ensure model keep working well after deployment, I need to monitor data pipeline on how key features like, mileage, fuel_type, car_age are changing overtime. If these shifts too much, tools like River, EvidentlyAI will be integrated into my system. Another step is to monitor performance by comparing it's predicted prices with actual price using RMSE and MAE. If these starts to drift, I'll retrain the model by inserting dataset into my ml pipeline which will automate on fixed schedule. Finally, i can improve by model by including time-based features like the car was sold or seasonal patterns which makes model aware of changing buyer behavior.

Legal, Ethical and Security Considerations

1. Data privacy

Though this dataset doesn't contain personal information and data is scraped from cars.com, it should be used only for academic and analysis purposes and not for activity leading to identifying individuals. Ensuring data privacy means respecting confidentiality of information and avoiding that could compromise the vehicles data as misuse.

2. Data security

It is the way we protect data from hackers, leaks, or people who shouldn't have access. This includes using passwords, encryption, and safe storage. Though this is scraped dataset, it should be stored in a secure location using authentication and authorization. Also, data encryption can be done after deployment and security can be maintained by restricting access to everyone.

3. Data ethics

It is about using data in a fair and honest way. In this dataset, ethical use means ensuring data is not misused, misrepresented, giving proper credit as taken from another source and misleading results due to biasness and limited data. By following these data ethics, we ensure honesty, transparency and respect in way we handle data.

4. Data protection laws are rules that companies must follow when they collect and use people's data. A popular one is GDPR in Europe, which gives people rights over their data. In this project, i ensure compliance by using data only for academic analysis, avoiding attempts to misuse and storing file securely. This helps in maintaining both legal and ethical standard in handling the dataset.

5. Essay on Differential Privacy

It is a data protection method used to protect individual information in a dataset while still allowing useful analysis. It works by adding a small amount of random noise to the data or it's result so it becomes very hard to identify any single vehicle from dataset. In this dataset containing details like brand, model, year, mileage and price, differential privacy would help ensure even if someone else tried to find information , they won't be able to do so accgfdsurately. This way overall patterns and trends in data remains useful for analysis and protected. Using differential privacy balance data utility with strong privacy protection.

6. Ethical & Practical Concerns with Mitigating Strategies

Since my dataset doesn't contain direct personal identifiers which reduces privacy concerns, the dataset was web scraped by creator had some ethical and practical problems that I fixed during preprocessing and model building. To protect privacy, I removed sensitive information like car IDs which was formed during star schema. Missing data were imputed using median and mode values to maintain reliability. I also standardized different data formats and changed categories into one-hot codes so the model treats them fairly.

To reduce bias regarding having very less electric vehicles leading to unfair pricing and make the model fairer, I used feature engineering and analyzed feature importance during model training to monitor their impact on my system. I tested the model carefully using train-test splits and 5-fold cross-validation to check its accuracy. To Ensure transparency and reproducibility, I used MLflow to track all experiments, also preventing misuse. In future if user ratings, reviews or preferences are incorporated I must manage consent, data ownership and limitation with privacy laws such as GDPR.

Overall, to address bias, transparency and future data protection, I plan to encrypt the data for deployment in web, implement user authentication and role based access to restrict who can train, modify and deploy models and develop consent management. These steps helps make sure the data was handled carefully and ready for building a good, ethical prediction model.

Reflections

This Coursework is a great learning experience that covered the full process of a machine learning project using MLOps. Choosing the right dataset showed how important it is to match data with project goals, especially when dealing with real-world problems like missing and inconsistent data. Careful cleaning and checking the data with tools like Great Expectations was essential.

In the visualization part, at first, i had put just random visualizations but after receiving feedback, i made changes to compare raw and preprocessed data, showing clearly how I handled missing values and improved data quality as details can be seen in fig;14, fig,345 and fig:w3

Building the MLOps setup with tools like Docker, MariaDB, Airflow, Redis, and MLflow was challenging but important for creating a reliable and repeatable pipeline. Designing the Airflow workflow to handle all steps from data loading to model training taught me a lot about automating complex processes.

Training the XGBoost model and deploying it through FastAPI made the project practical and useful. Exploring the data helped improve the model and understand its results. The project also raised important legal and ethical issues, like dealing with biased or web-scraped data, reminding me of the responsibility in building such systems.

The biggest challenge was setting up and fixing problems with all the different tools working together, mainly while I was training model, that was the most hectic for me because model took very long time to train. Later I realized it was stuck in between, the model wasn't trained at all which took time and patience.

Also, I made various changes based on feedback received from my coordinator which included clarifying ground truth, ETL, enhancing visualization pipeline, Data analysis and ERD Diagram. Lastly, from the right guidance from my coordinator's sample and friends, helped me find errors to complete this work.

Conclusion, Recommendation and Future Work

This report successfully demonstrates the Used car price prediction system using real-world scraped data and ML tools. This started by collecting, ingesting and cleaning data, checking it's quality using great expectations and stored in structured way. Then, trained model using XGBoost with Optuna Hyperparameter Tuning to predict model and deployed usinf FastAPI. One major point was learning system that are automatic and easy to maintain which was possible using airflow pipeline overcoming all those challenges. Beside building a working system, it ma

To keep the system working well overtime, it should be retrained automatically when the data changes and to focus on fairness and transparency using LIME or SHAP to show why model predicted this price. Also, we can spend more time on create features for the model as the need arises. While MariaDB and Redis worked well for this project. The future version could include cloud based servers for storage, creating simple web interface with Streamlit or Flask would make it more easier. The system could explore more models like LightGBM or CatBoost to see if they give better results. Another good step would be to detect data drift more smartly trying online learning where model updates itself when new data arises instead of retrained from scratch which is main motive of the pipeline, which would help the system stay current and responsive.

Lastly, with data from 1974-2024, I was able to build a model that predicts future car price trends adding more value for users.

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