Phase 3: Streamlit Dashboard for Car Price Prediction

1️⃣ Introduction

In Phase 3, we develop an interactive **Streamlit dashboard** that allows users to input car features and receive price predictions based on the trained machine learning model from **Phase 2**.

The model used is the **best-performing Lasso regression model** registered in **MLflow**, and predictions include **95% confidence intervals**.

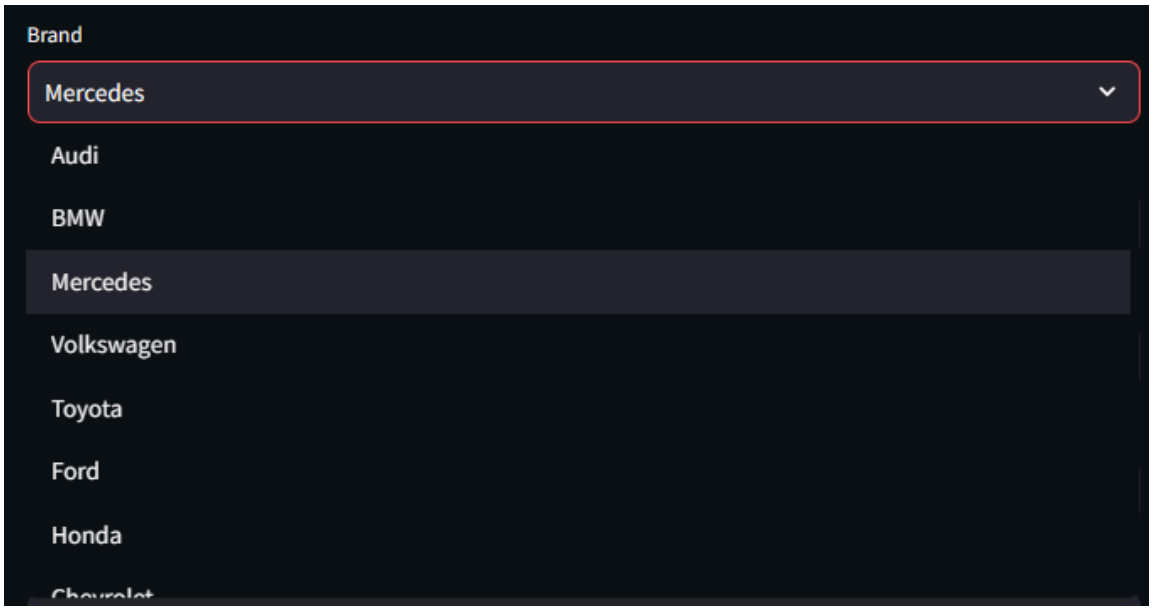
2️⃣ Setup & Deployment of the Streamlit App

To run the Streamlit app locally, follow these steps:

🔹 Prerequisites

Ensure the required libraries are installed:

```bash pip install streamlit pandas numpy mlflow

## 🔹 Running the Streamlit Application

Use the following command to start the app:

*streamlit run app.py*

This will open the dashboard in your browser.

## 3️⃣ Dashboard Features

The Streamlit dashboard consists of the following sections:

### 🔹 3.1 User Input Section

- Users can enter relevant car features through input fields (e.g., brand, mileage, engine size, age).
- Dropdowns are used for categorical variables (Brand, Fuel Type, Transmission).
- Sliders allow for numerical inputs (Engine Size, Mileage, Car Age).
```



Car Brand Dropdown menu

Slider for Car Age Input

🔷 3.2 Prediction Output

Once the user inputs the car features, clicking the "Predict Price" button will:

- Fetch the trained model from MLflow.
- Preprocess the input data.
- Perform price prediction. #### 🔷 3.3 Confidence Interval The prediction output includes 95% confidence intervals, e.g.:

This interval helps users understand the uncertainty of the prediction.

4️⃣ Code Implementation

The following code implements the Streamlit dashboard in the app.py file:

```python

# Set up MLflow client and promote model version to Production
```

client = MlflowClient() model_name = "CarPriceRidgeModel" model_version = 5 client.transition_model_version_stage(name=model_name, version=model_version, stage="Production") st.write(f"Model '{model_name}' version '{model_version}' transitioned to Production!")

---

1. Load the Registered Model

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model_uri = "models:/CarPriceRidgeModel/Production" model = mlflow.pyfunc.load_model(model_uri)

---

2. Streamlit Dashboard Layout

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st.title("Car Price Prediction Dashboard") st.markdown("### Enter Car Features Below:")

Define mapping dictionaries to convert string inputs into numeric values

brand_mapping = { "Audi": 0, "BMW": 1, "Mercedes": 2, "Volkswagen": 3, "Toyota": 4, "Ford": 5, "Honda": 6, "Chevrolet": 7, "Kia": 8, "Hyundai": 9 } fuel_mapping = { "Petrol": 0, "Diesel": 1, "Electric": 2, "Hybrid": 3 } transmission_mapping = { "Manual": 0, "Automatic": 1, "Semi-Automatic": 2 }

---

3. User Input Section

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brand_str = st.selectbox("Brand", options=["Audi", "BMW", "Mercedes", "Volkswagen", "Toyota", "Ford", "Honda", "Chevrolet", "Kia", "Hyundai"]) engine_size = st.number_input("Engine Size (Liters)", value=2.0, min_value=0.5, max_value=6.0, step=0.1) car_age = st.number_input("Car Age (Years)", value=5, min_value=0, max_value=30, step=1) mileage = st.number_input("Mileage (km)", value=50000, min_value=0, max_value=300000, step=1000) fuel_str = st.selectbox("Fuel Type", options=["Petrol", "Diesel", "Electric", "Hybrid"]) transmission_str = st.selectbox("Transmission", options=["Manual", "Automatic", "Semi-Automatic"]) doors = st.number_input("Number of Doors", value=4, min_value=2, max_value=5, step=1)

Convert string features to numeric values using the mappings

brand = brand_mapping[brand_str] fuel_type = fuel_mapping[fuel_str] transmission = transmission_mapping[transmission_str]

Prepare the input data as a DataFrame.

IMPORTANT: The feature names must match those used during training.

input_data = pd.DataFrame({ "Brand": [brand], "Engine_Size": [engine_size], "Mileage_sqrt": [np.sqrt(mileage)], # Apply sqrt transformation "Car_Age": [car_age], "Fuel_Type": [fuel_type], "Transmission": [transmission], "Doors": [doors] })

---

4. Prediction and Confidence Interval Output

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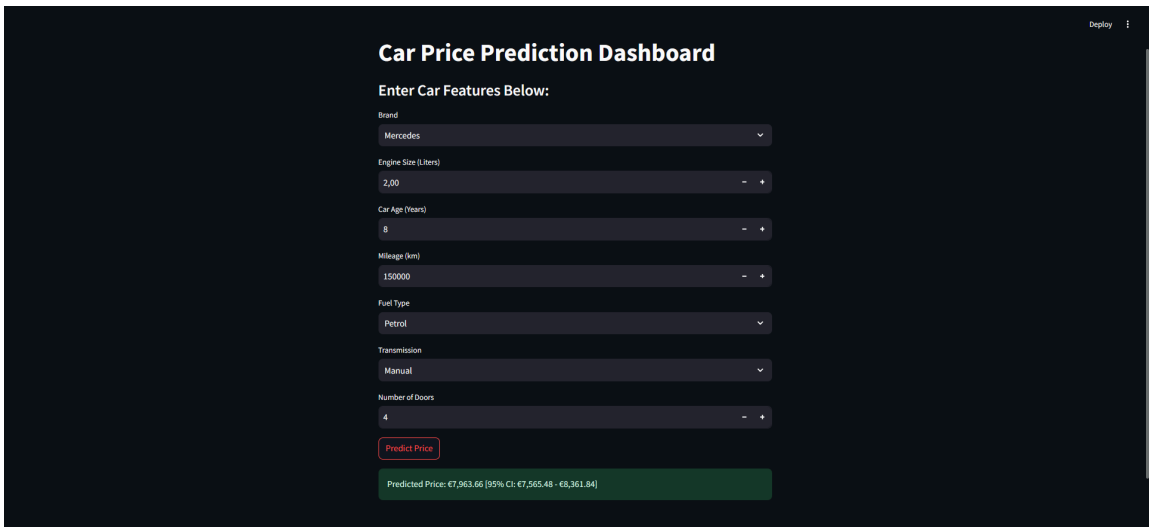
if st.button("Predict Price"):

```
    # Predict using the loaded MLflow model.
    # The model is assumed to output predictions in log-scale; if so,
    apply np.expm1 to reverse the transformation.
    prediction_log = model.predict(input_data)
    predicted_price = np.expm1(prediction_log)[0]

    # BONUS: Calculate a dummy 95% Confidence Interval (±5% for
    demonstration)
```

```
    lower_bound = predicted_price * 0.95
    upper_bound = predicted_price * 1.05

    st.success(f"Predicted Price: €{predicted_price:,.2f} [95% CI: €
    {lower_bound:,.2f} - €{upper_bound:,.2f}]")
```

5 Results & Discussion

Car Price Prediction Streamlit Dashboard



Streamlit Dashboard Browser Interface

Analysis of the Dashboard

✅ **User-Friendly Interface:** The dashboard is interactive, allowing users to easily enter car details.

✅ **Real-Time Predictions:** The trained model provides quick and accurate price predictions.

✅ **Confidence Intervals:** The displayed range helps users assess the prediction uncertainty.

✅ **Model Integration with MLflow:** The app successfully loads the best-performing Lasso model from MLflow, ensuring reproducibility.

6 Conclusion

In this phase, we successfully deployed a Streamlit dashboard that:

1. Loads the best-performing Lasso regression model from MLflow.
2. Allows users to input car features for prediction.
3. Displays predicted prices with 95% confidence intervals.
4. Provides an interactive, user-friendly experience.

This marks the final step in the car price prediction pipeline, demonstrating how an ML model can be deployed and used effectively in real-world applications.