AI Predictive Maintenance Development Document

Objective: Enhance vehicle safety and efficiency by predicting maintenance needs using an AI-driven system before issues escalate, reducing downtime and maintenance costs.

System Architecture and design document: Please refer document below-

AI_Driven_Vechicle_Design_Document

Detailed Component Overview:

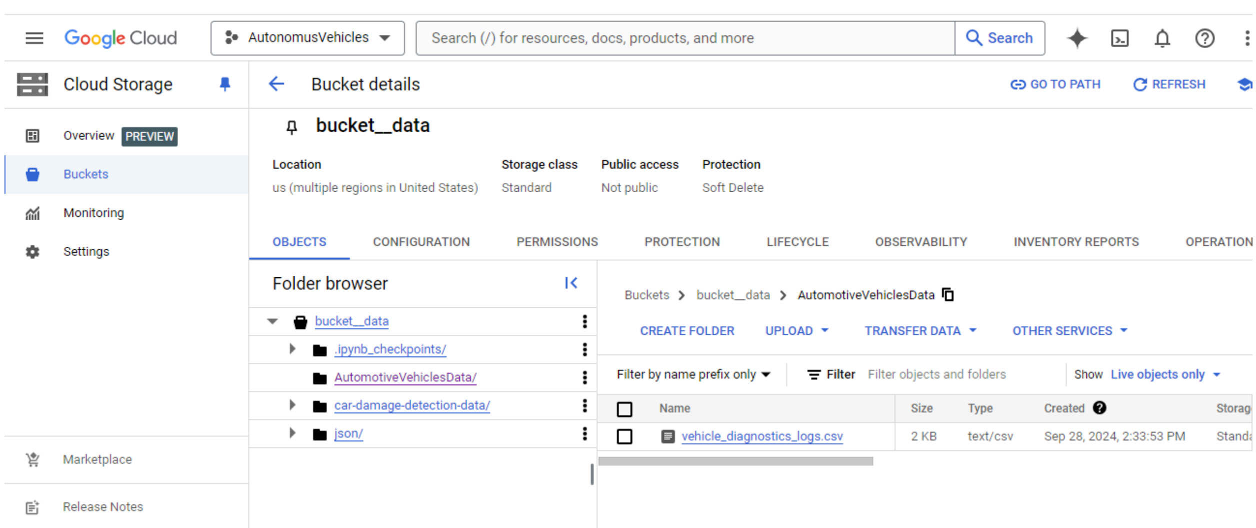
1) NLP for Diagnostic Logs-

Functionality Overview: This component processes these logs to extract actionable insights, aiding in early diagnosis and prevention of potential failures.

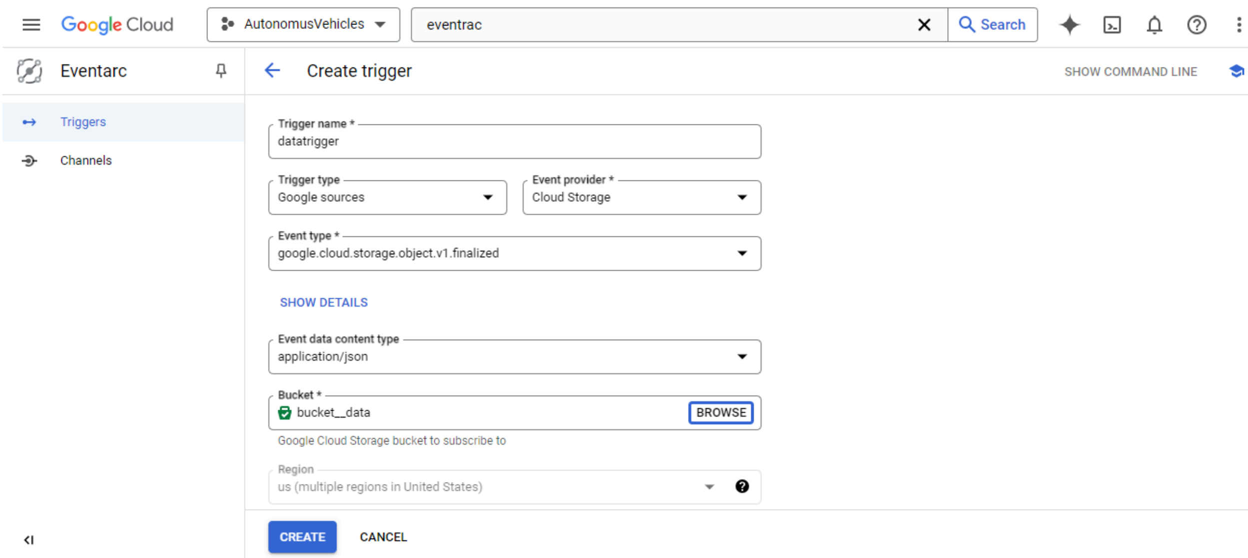
Technical Implementation:

a) Data Ingestion Pipeline:

- Set up Google Cloud Storage to store vehicle sensor data and diagnostic logs.

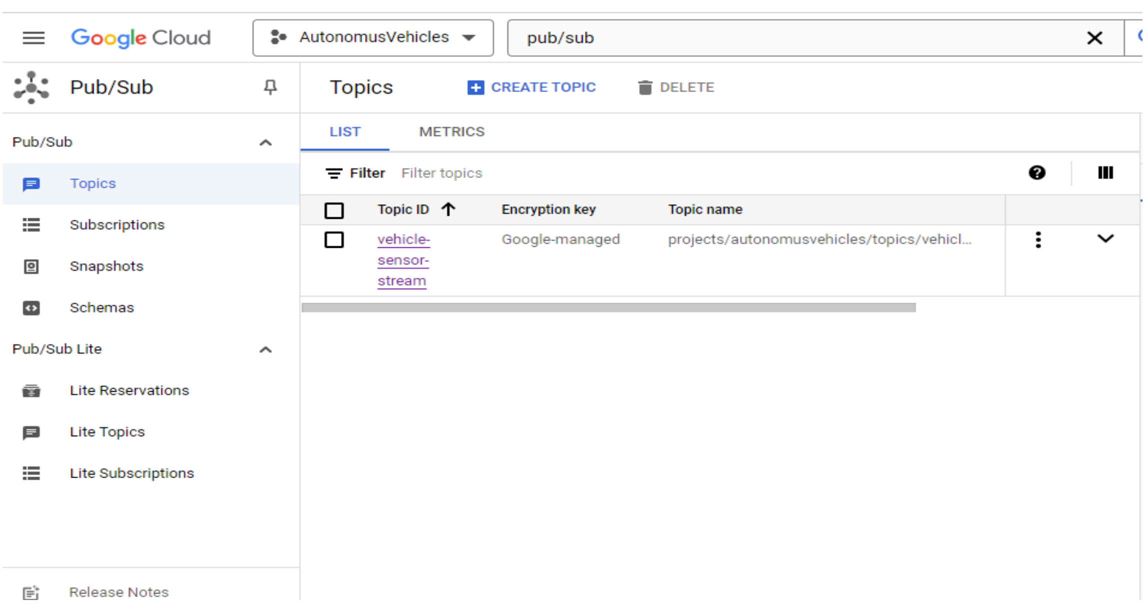


- **Create an Event trigger** via Eventarc trigger which automatically invokes the `publish_vehicle_logs` function whenever a new file is uploaded to the specified bucket in Google Cloud Storage.

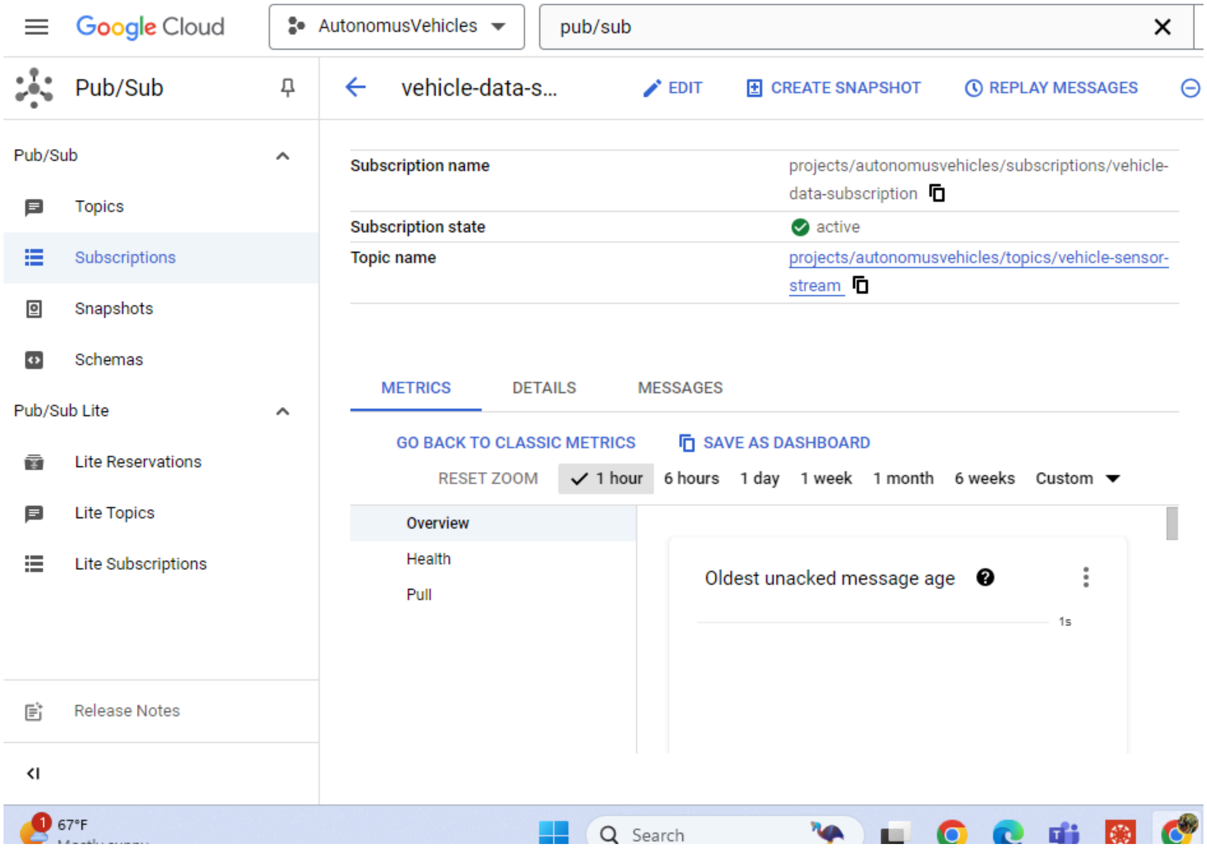


Publish vehicle logs function- [publish_vehicle_logs.py]

Create a Pub/Sub topic to receive notifications of new entries added to Cloud Storage. Acts as a messaging service to trigger the processing function whenever new log data is available.



Set up a subscription to this topic that triggers a Cloud Function whenever new data is published.

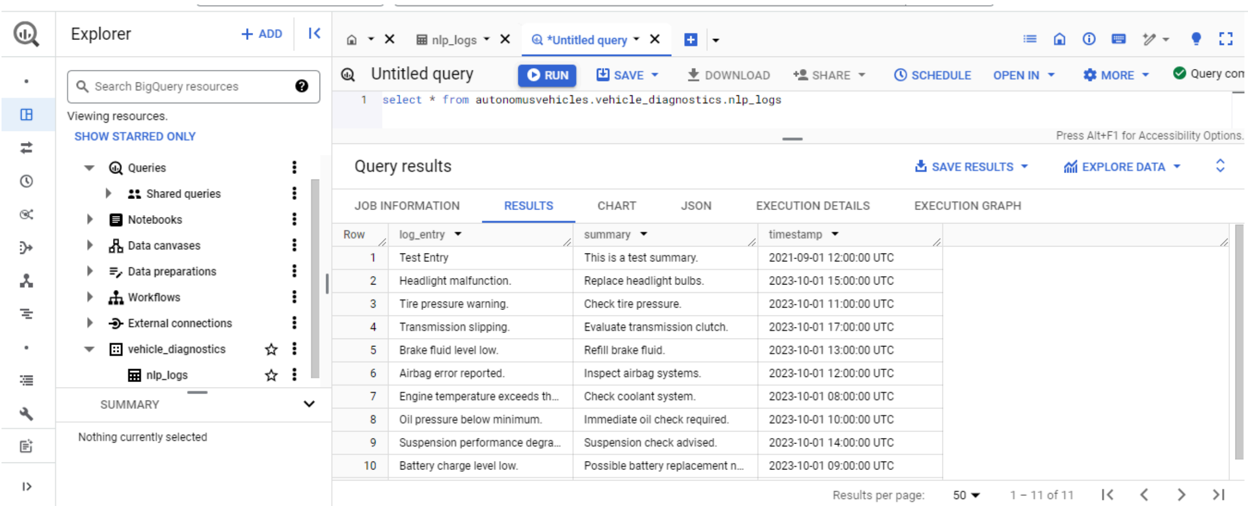


- Use **Cloud Functions** to analyze logs to summarize key issues and publish the data to Pub/Sub.

Steps:

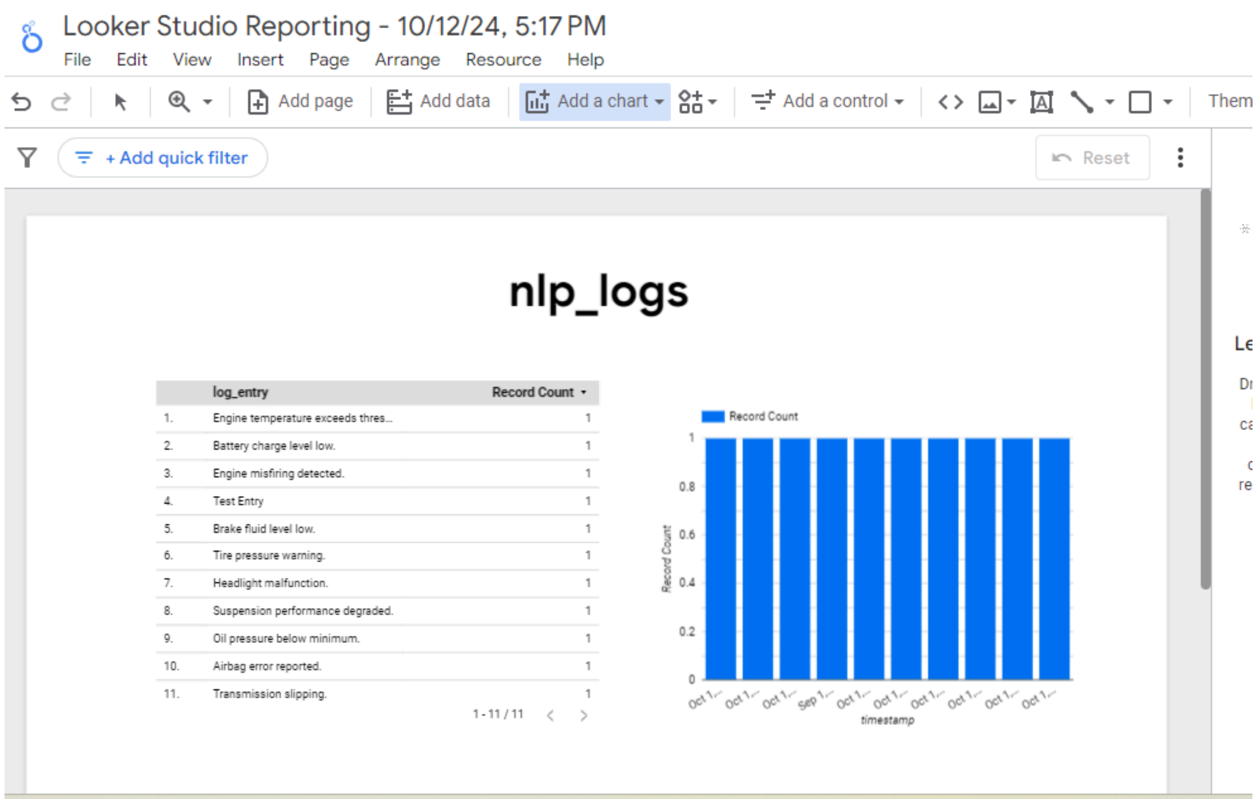
1. Develop a Python function using the Natural Language Toolkit (NLTK) to process and analyze text.
2. Deploy this function in Google Cloud Functions, triggered by the Pub/Sub subscription.
3. Function writes processed data to Google BigQuery for further analysis and historical tracking.

Process nlp functions- process_nlp_function



Theoretical Final Steps:

- **Data Integration-** Connect Looker Studio to BigQuery to automatically pull in real-time NLP processed data for immediate analysis.



- **Dashboard Design-** Design a user-friendly dashboard that displays critical metrics like error frequency, issue types, and urgent alerts through easy-to-read charts and conditional color coding.

- **Alert Simulation-** Set theoretical thresholds for alerts that, when exceeded, highlight urgent issues on the dashboard to prompt immediate attention.

2) Computer vision module

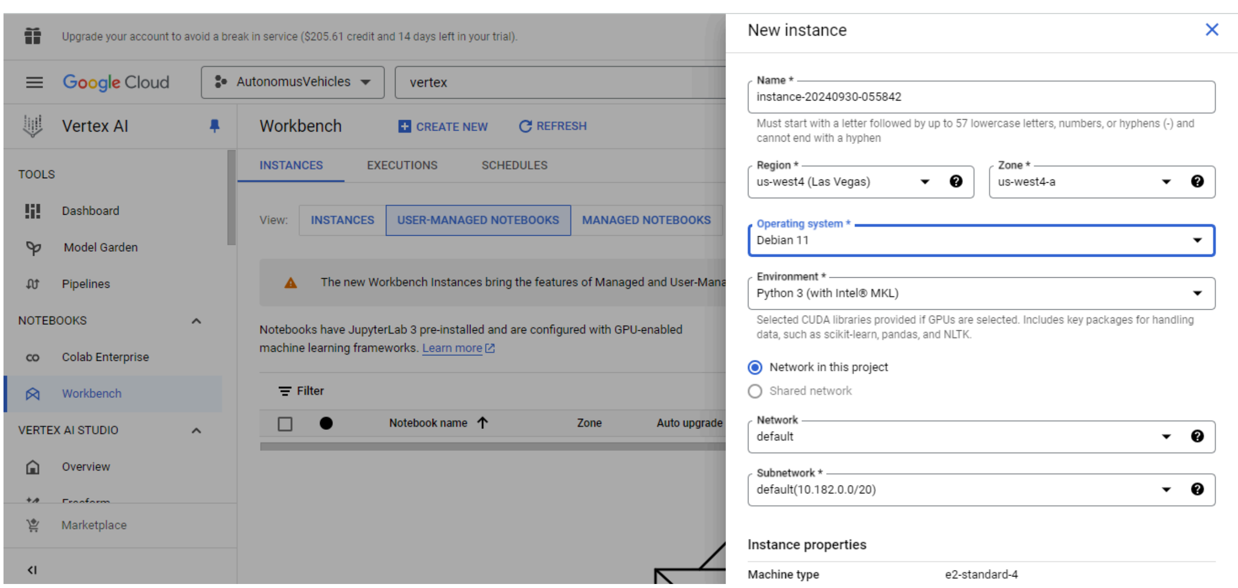
Objective: Develop a Computer Vision system that analyzes images from vehicle cameras to detect signs of wear, damage, or other maintenance needs before they lead to failure.

Technical Implementation:

1. **Data Collection and data storage:** Set up onboard cameras in strategic locations on the vehicle to capture images of critical components and areas. Configure Google Cloud Storage to store and manage the large volumes of image data collected from vehicles. [COCO Damage Detection - Trained Models.](#) This dataset provides pretrained models that are trained on the COCO dataset, specifically fine-tuned for damage detection.

2. **Choose a Pre-Trained Model**: You can use a **pre-trained YOLOv5 model** from **TensorFlow**.

3. **Create a Vertex AI Workbench** (Notebook Instance) Navigate to Vertex AI: From the Navigation Menu, go to AI/Vertex AI > Workbench > User-managed notebooks. Create a new dataset configuration file car_damage.yaml to point to the Cloud Storage paths. Install YOLOv5 in the Notebook to read from the bucket. [car_damage.yaml](#)



4**. Test YOLOv5 with Your Dataset:** Use the YOLOv5 detection script to run inference on a few validation images from the dataset.

python detect.py --weights yolov5s.pt --img 640 --conf 0.25 --source gs://bucket__data/car-damage-detection-data/validation/00-damage

This will run YOLOv5's inference on the images and display the damaged part of cars.

5. **Visualize the Output** After running the inference, YOLOv5 will output images with bounding boxes drawn around detected objects. These images will be saved in the **runs/detect/exp** folder in your YOLOv5 directory.

Workspace: [Workspace]

6. **Train the YOLOv5 Model:** Run the YOLOv5 training command with the configuration file created earlier (`car_damage.yaml`):

python train.py --img 640 --batch 16 --epochs 50 --data car_damage.yaml --weights yolov5s.pt --cache

7. **Deploy the Model:** The trained YOLOv5 model is deployed as a Google Cloud Function. This function processes images from the car's cameras, detecting damage when it occurs.

8. **Analyze and Notify:** The Cloud Function analyzes the images and, upon confirming damage, sends a notification with the details (e.g., type and extent of damage) to the car owner's mobile app.

3) Physics-Informed Neural Networks (PINNs)

Objective: The goal is to develop a Physics-Informed Neural Network (PINN) that predicts vehicle component wear and stress over time based on sensor data (temperature, pressure, vibration). The model will simulate the physical behavior of vehicle components (e.g., engine, brakes) and predict failure times, allowing for proactive maintenance.

Tools:

- **Vertex AI Workbench**: This platform provides a managed environment for developing machine learning models. We use it to train and deploy our PINN.
- **TensorFlow**: A machine learning library used to define, train, and deploy the PINN model.
- **NumPy**: A library for numerical operations, used here to simulate sensor data and perform mathematical operations.
- **SciPy**: Useful for solving differential equations and integrating scientific computing tasks into the model.
- **Matplotlib**: A plotting library to visualize the simulated data and model predictions.

Functionality: A PINN integrates physical laws (like differential equations) into the structure of a neural network. It will simulate the behavior of specific car components (e.g., engine, brakes) and predict how long they will last based on real-world data.

- Vertex AI Workbench is used for development. PINNs can be implemented using TensorFlow along with some scientific libraries for physics-based simulations.Ensure the required libraries are installed: TensorFlow, SciPy, Matplotlib, NumPy, and other necessary scientific libraries.
- Kaggle Data: AI4I 2020 predictive maintenance dataset is used. The data includes:Temperature, pressure, vibration, and wear information over time.
- Define a PINN architecture in TensorFlow. PINN will solve a differential equation like heat transfer or stress analysis and predict the time to failure.
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  Simulate Vehicle Component Data: We need to simulate historical vehicle data that reflects how certain components degrade over time. For example, we can simulate temperature, pressure, or vibration data from sensors in the vehicle. In real time, this component would receive real-time sensor data from the vehicle's onboard diagnostic system and predict when a part is likely to fail.

- Train the PINN Model: We train the PINN model to predict when a component will fail based on simulated data (e.g., temperature or pressure changes over time). The training process uses historical data and physical laws (e.g., stress-strain relationships) to predict failure points. Train the PINN model using the simulated data.

- Evaluate and Predict Failure Time: PINN can predict how much longer a component will last before failure. For example, we can feed the model new sensor data and predict when a specific part (like the engine or brakes) might overheat or break down. In real time: The model continuously monitors the vehicle’s sensor data and provides real-time predictions on when maintenance is required.

Steps:

Step 1: Environment Setup

- Libraries: TensorFlow, SciPy, NumPy, Matplotlib.
- Method: Use pip to install libraries in the Jupyter notebook environment on Vertex AI Workbench.

Step 2: Simulate Vehicle Component Data

- Libraries: NumPy, Matplotlib.
- Method: Use np.linspace() to simulate time intervals and np.random.normal() to add random noise to the data. Visualize the data using plt.plot() from Matplotlib.

Step 3: Define the PINN Architecture in TensorFlow

- Library: TensorFlow.
- Method: Use Sequential() to create a neural network model with Dense() layers for input, hidden, and output layers. Activation functions like tanh and linear are applied.

Step 4: Incorporate Physics Laws into the Loss Function

- Library: TensorFlow.
- Method: Use GradientTape() to compute derivatives required for the physics-informed loss function. Use tf.reduce_mean() to calculate the residuals for physical laws and the data loss.

Step 5: Train the PINN Model

- Library: TensorFlow.
- Method: Use compile() to define the optimizer (Adam) and loss function. Train the model using fit() by providing the training data and specifying epochs and validation split.

Step 6: Predict Component Failure

- Libraries: TensorFlow, Matplotlib.

- Method: Use predict() to forecast component behavior based on new sensor data. Use Matplotlib's plt.plot() to visualize predictions and determine failure points by defining a threshold.

Step 7: Deploy the Model on Vertex AI

- Library: Google Cloud AI Platform (aiplatform).
- Method: Use Model.upload() to upload the trained model to Vertex AI and deploy() to create an endpoint for real-time predictions.

Step 8: Real-Time Predictions and Alerts

- Libraries: Vertex AI, Custom API for Alerts.
- Method: Ingest real-time sensor data and feed it into the deployed model for continuous predictions. When failure is predicted, trigger an alert via a mobile app or dashboard using API-based alerts.

Code : Code link

Integration steps of PINN model:

Data Ingestion from Real-Time Sensors:

- **Goal**: Set up a mechanism to collect real-time sensor data (temperature, pressure, vibration) from the vehicle.
- **Approach**: Use **Google Cloud IoT** or edge computing to ingest and process real-time data from the vehicle's onboard diagnostic system.

Event-Driven Architecture:

- **Goal**: Set up triggers to automatically run predictions when new sensor data is available.
- **Approach**: Implement **Google Cloud Pub/Sub** or **Eventarc** to trigger predictions when new logs or sensor data are uploaded.

Integration of Notifications:

- **Goal**: Create a notification system to alert car owners of imminent component failure.
- **Approach**: Use an API to send alerts via a **mobile app** or in-car **dashboard**. Could be based on Google Firebase for app notifications or in-car infotainment systems for dashboard alerts.

Evaluation Metrics:

- **Goal**: Define evaluation metrics to assess the performance of the model (e.g., Mean Squared Error, R^2, precision of failure predictions).
- **Approach**: Track metrics during training and testing using TensorFlow's built-in evaluation methods and adjust hyperparameters to improve the model.