# SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

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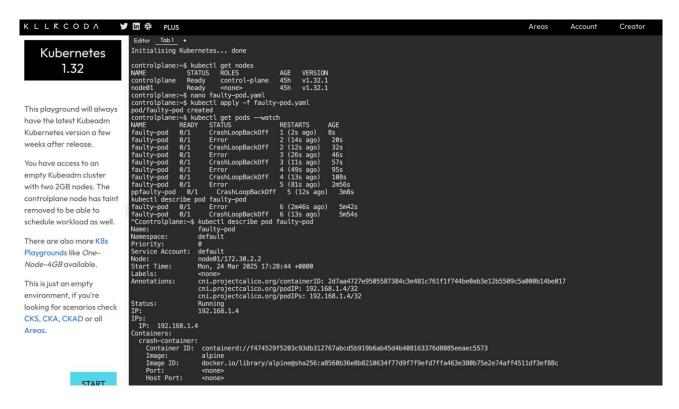
#### **Problem Statement:**

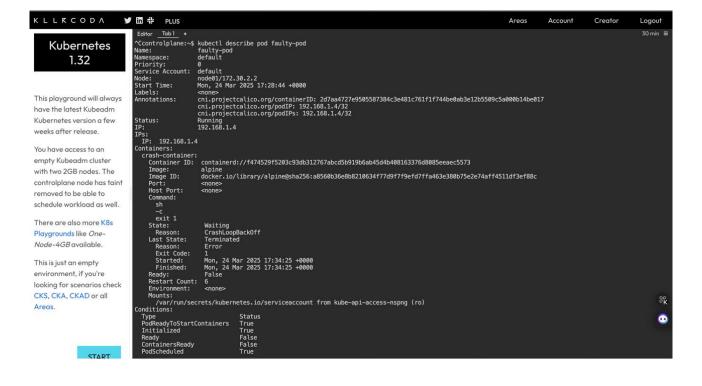
Kubernetes clusters often face issues like **pod failures**, which lead to service downtime and degraded system performance. Detecting these failures early is crucial for maintaining system stability.

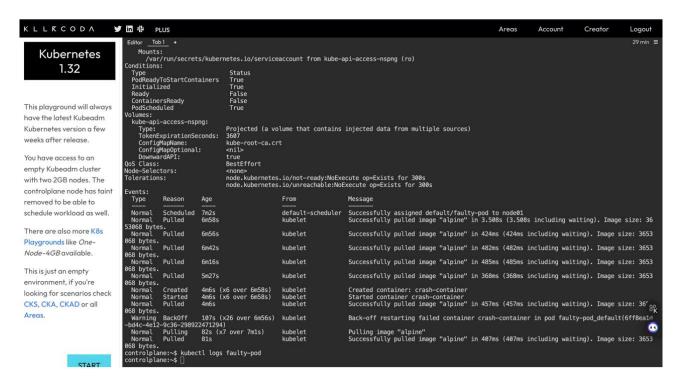
## **Our Approach:**

For this hackathon, our team focused on **predicting Kubernetes pod failures** using a Machine Learning model. After analyzing various possible issues, we found that **pod failure prediction**— especially detecting failures like CrashLoopBackOff—was the most feasible and impactful to solve within the timeframe.

STEP 1: Creation of a Pods failure for the visual representation







#### STEP 2: Dataset Creation

We generated a dataset by collecting Kubernetes pod metrics such as:

- Timestamp
- Namespace
- Pod Status (Running, CrashLoopBackOff, Failed, etc.)
- Restart Count
- CPU Usage
- Memory Usage

We simulated pod failures by:

- Increasing the restart count beyond safe thresholds
- Assigning failure statuses like CrashLoopBackOff
- Injecting resource-heavy conditions (high CPU and memory usage)

Feature Engineering:

We enhanced the dataset with additional features: V Hour of the Day

- **V** Day of the Week
- Resource Stress Score (based on CPU > 1.5 cores or Memory > 400MB)
- Namespace Historical Risk (calculated from past failure data per namespace)

### STEP 3: Model Training

We used a **Random Forest Classifier** to train the model.

Data was split into training and testing sets, and scaled using **StandardScaler** for better model performance.

## **Training Highlights:**

- Balanced class weights to handle imbalanced data
- High accuracy in predicting failure-prone pods
- Evaluated using Confusion Matrix and Classification Report

#### **Prediction Process:**

For any new pod, the model:

- 1. Takes real-time pod metrics (CPU, Memory, Restarts, etc.)
- 2. Computes the resource stress and historical namespace risk
- 3. Predicts whether the pod is likely to fail
- 4. Provides the **probability of failure**

## **Example Output:**

Will Fail: Yes

V Failure Probability: 85.34%

```
(venv) aditya@Adityas-MacBook-Air-6 test % python -u "/Users/aditya/projects_all/test/test.py"
Classification Report:
               precision
                              recall f1-score
                                                   support
                     0.75
                                0.88
                                           0.81
            1
                     0.89
                                           0.83
                                                        112
                                                        200
                                           0.82
0.82
                     0.82
                                0.83
   macro avg
weighted avg
                     0.83
                                0.82
Confusion Matrix:
[[77 11]
[25 87]]
Pod Failure Prediction:
Will Fail: False
Failure Probability: 38.00%
(venv) aditya@Adityas-MacBook-Air-6 test % □
                                                                                        Aditya Gupta (40 minutes a
```

### Why This Solution is Effective:

- ✓ Combines real-time metrics with historical data
  - ✓ Detects potential failures **before they happen**
  - √ Helps DevOps teams prevent downtime
  - ✓ Scalable and can be integrated into **Kubernetes monitoring tools**

# **Future Scope:**

- Integrate with live Kubernetes clusters for real-time predictions
- Add alerting systems based on failure probability thresholds
- Extend the model to predict other Kubernetes issues like **node failures**, **OOM kills**, etc.