

# Equipment Maintenance Monitoring and Analysis

A Comprehensive System for  
Performance Analysis, and  
Maintenance Planning



Name:

- Divija Joshi
- Devishree Jadhao

SIIL-TEAM-0025

# Introduction

Predictive maintenance applies machine learning and sensor data to predict failures before they happen in order to improve productivity, efficiency, and cost-effectiveness. Differing from traditional methods of maintenance, PdM studies real-time data such as temperature or vibration and, having detected anomalies or foreseeing problems, precludes downtime of up to 30-50%. This sort of technology lets conduct condition-based maintenance, as schedules are optimized and the need for unnecessary interventions is prevented. The main work is done in anomaly detection, real-time reporting, and dashboard development by machine learning, but obstacles like data quality and equipment variability exist. It aims to provide its benefits to maintenance teams so that these teams can enhance their operational efficiency according to the trend of Industry 4.0.

# Objectives

- **Build and Test Machine Learning Models:** Construct many predictive models and compare them by evaluating the most accurate and efficient model for equipment failure prediction and RUL estimation.
- **Causal Analysis:** Apply causal analysis on the root causes of equipment failures to understand the dominant factors that can be leveraged for targeted maintenance and process improvement.
- **Develop an Interactive Dashboard:** Create an interactive dashboard that presents equipment health, remaining useful life, and recommended maintenance actions in real time to anticipate better decisions by the maintenance teams.
- **Support Data-Driven Maintenance:** Ideally, enable a shift to proactive, data-driven maintenance practices that can reduce downtime while also extending equipment lifespans and equate to the yardstick of achieving Industry 4.0 goals.

# Features:

## Real Time Alerts:

01

**Immediate alerts** are triggered for equipment needing maintenance based on real-time data.

02

**Visual Suggestion:** An alert box example displaying "⚠️ 3 equipment units require immediate attention!"

**03**

## **Interactive Equipment Explorer**

Users can select key metrics such as Temperature Difference, Tool Wear, Power, Torque, and Rotational Speed. Adjustable time window slider for viewing recent observations.

**04**

## **Performance Analysis**

Classification report for failure prediction accuracy. Precision-Recall curve showing model trade-offs. Highlights which features are most impactful in predictions.

**05**

## **Correlation Analysis**

Calculates correlation between features for insights on interdependencies. Heatmap visually represents these relationships.

06

## **Maintenance Planning**

Predicts next maintenance dates based on tool wear and failure risk. Prioritizes high-risk equipment for maintenance to reduce downtime. Estimated maintenance costs for budget planning.

07

## **Maintenance Cost Projection**

Users enter the estimated cost per maintenance task. Total projected cost calculated by multiplying task count by unit cost. Comparison to budget to gauge any cost overruns or savings.

08

## **Historical Performance Analysis**

Historical Trends: Users can review past performance of key metrics to identify patterns.

Failure Patterns: Analysis of common causes for equipment failure.

Visual Suggestions: Line chart with trend lines for historical data and failure pattern metrics for each major cause.

**09**

## **Recommendations and Best Practices**

Adjust alert thresholds to align with equipment health metrics. Regular model retraining improves prediction accuracy. Contact the maintenance team for immediate issues flagged by the system.

**10**

## **Generate and Download Maintenance Report**

Create a report with maintenance data: failure risk, tool wear, maintenance priority, and next maintenance date. Export as CSV for offline analysis and documentation.

# Methodology

## Problem Definition & Objectives

- Address equipment breakdowns in manufacturing by forecasting failures, optimizing maintenance schedules, and enabling real-time monitoring.

## Data Collection & Preprocessing

- Used a Kaggle dataset with equipment metrics. Cleaned data, handled missing values, and created features (e.g., temperature difference, rolling means) to improve model accuracy.

## Model Selection & Training

- **Random Forest Classifier:** Predicts failure risk.
- **Gradient Boosting Regressor:** Forecasts tool wear.
- Evaluated with precision-recall, RMSE, and feature importance to ensure reliability.



# Methodology

## Dashboard Development

- Built using Streamlit with Plotly for visuals. Includes:
  - **Real-Time Monitoring:** Live metric tracking.
  - **Performance Analysis:** Model metrics and correlation heatmaps.
  - **Maintenance Planning:** Timeline for risk-based maintenance actions.

## Deployment & Usage

- Hosted on Hugging Face Spaces with pre-trained models cached for faster load times.
- Users can adjust model settings, thresholds, and view scheduled maintenance predictions. Future enhancements include IoT data integration and real-time alerts.

## Technology Stack

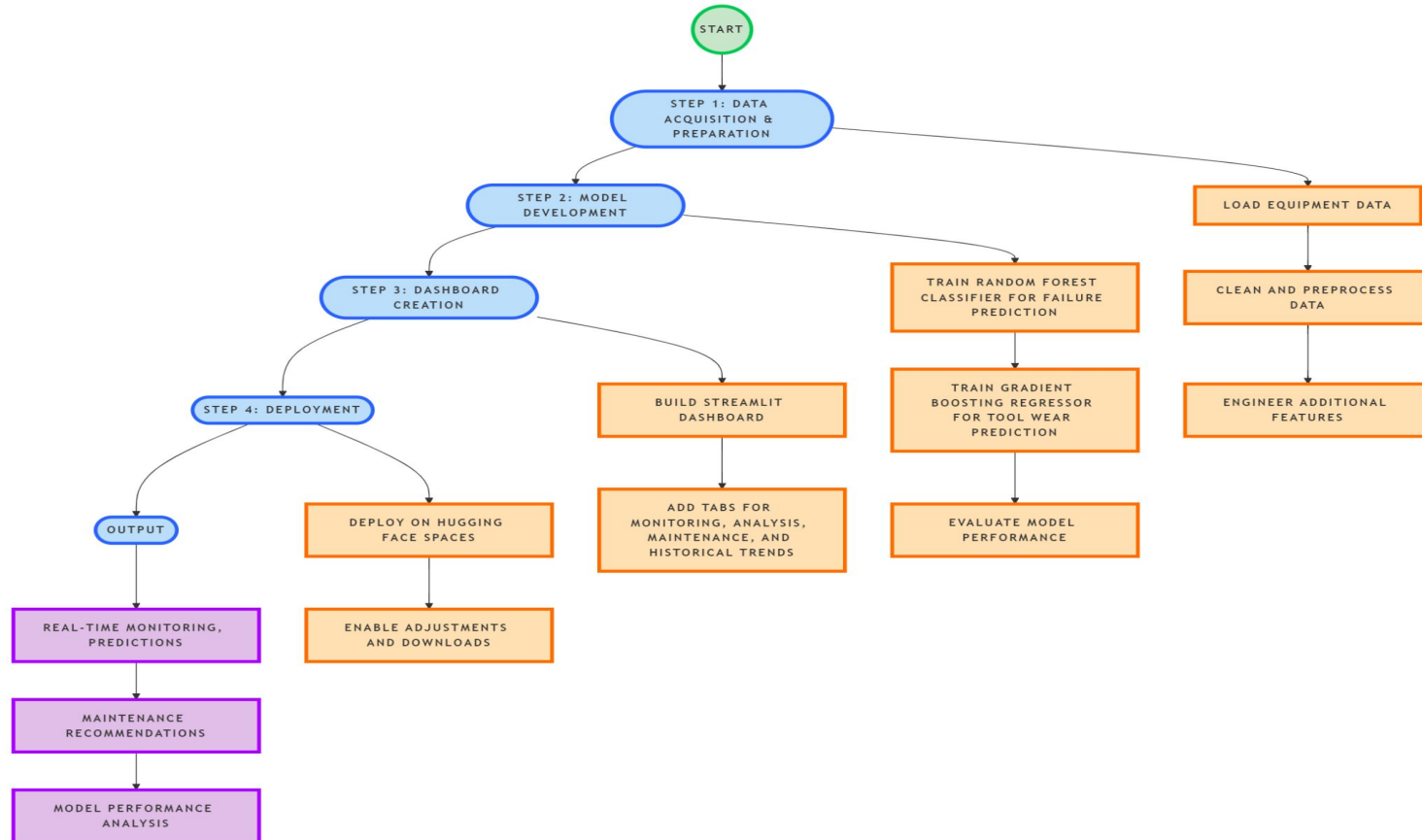
Frontend: Streamlit for interactive dashboard UI

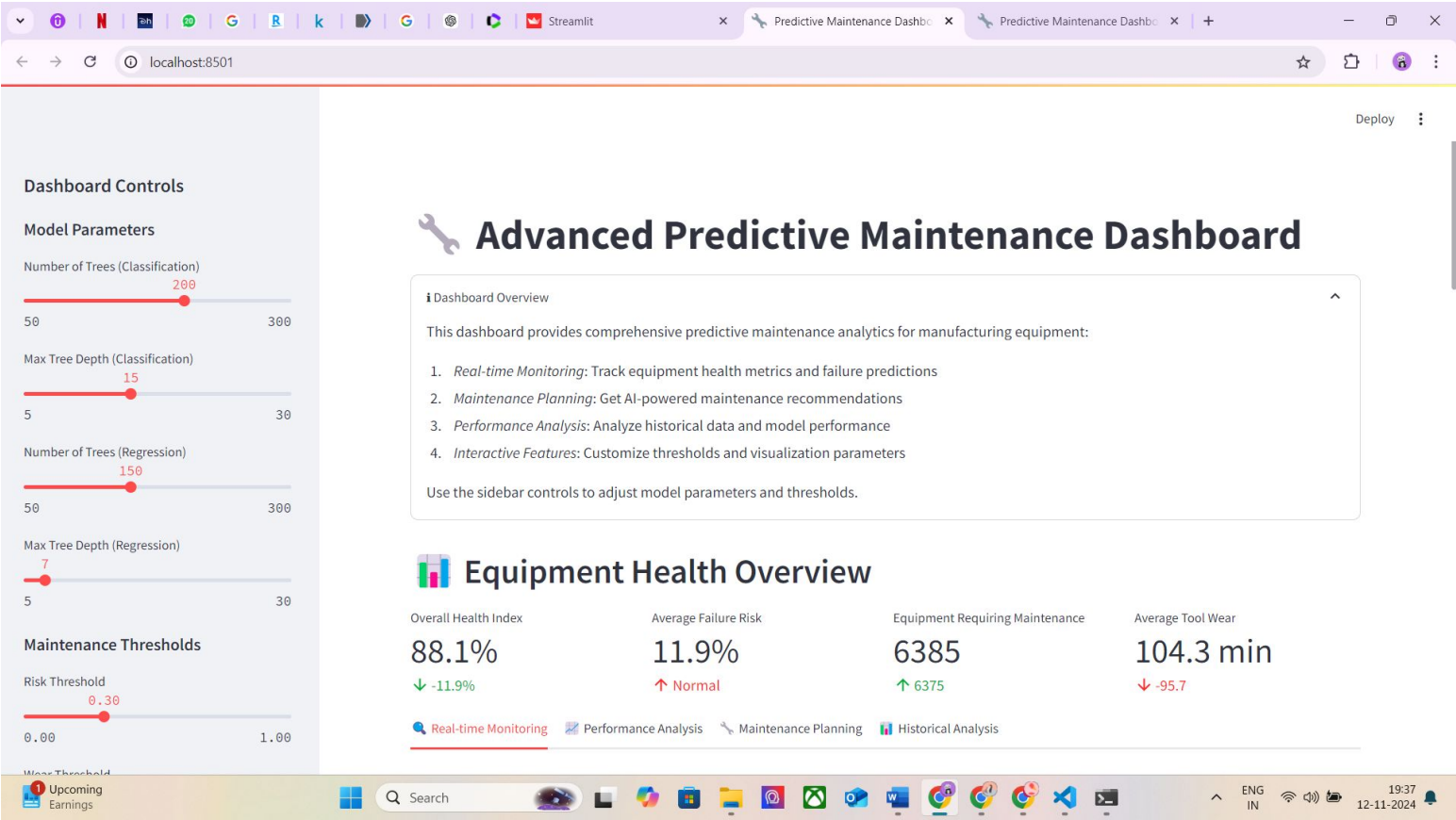
Data Processing & Modeling: Scikit-learn for machine learning, Pandas for data manipulation, and NumPy for numerical operations

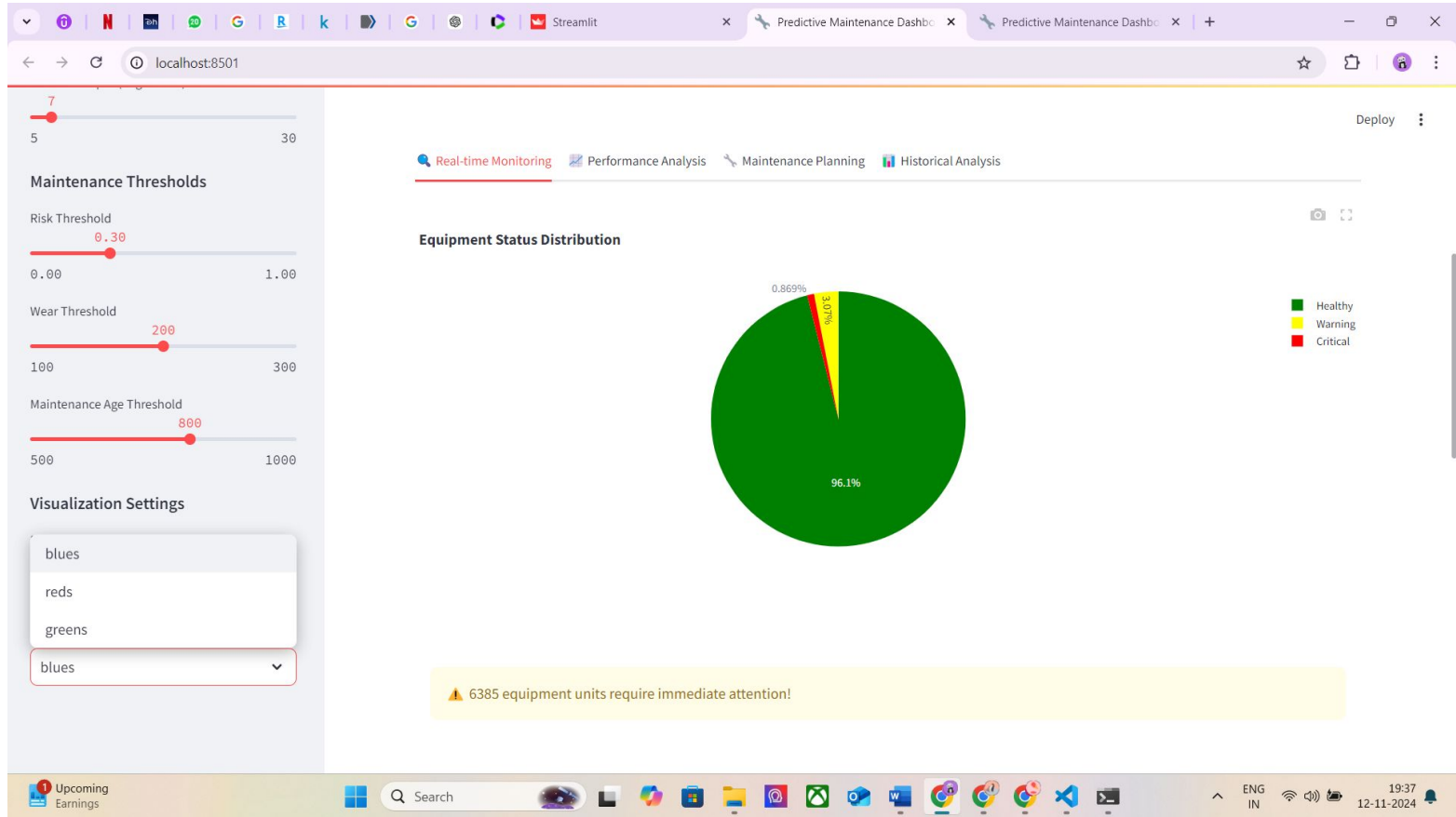
Visualization: Plotly for interactive data visualizations and Seaborn for static plots

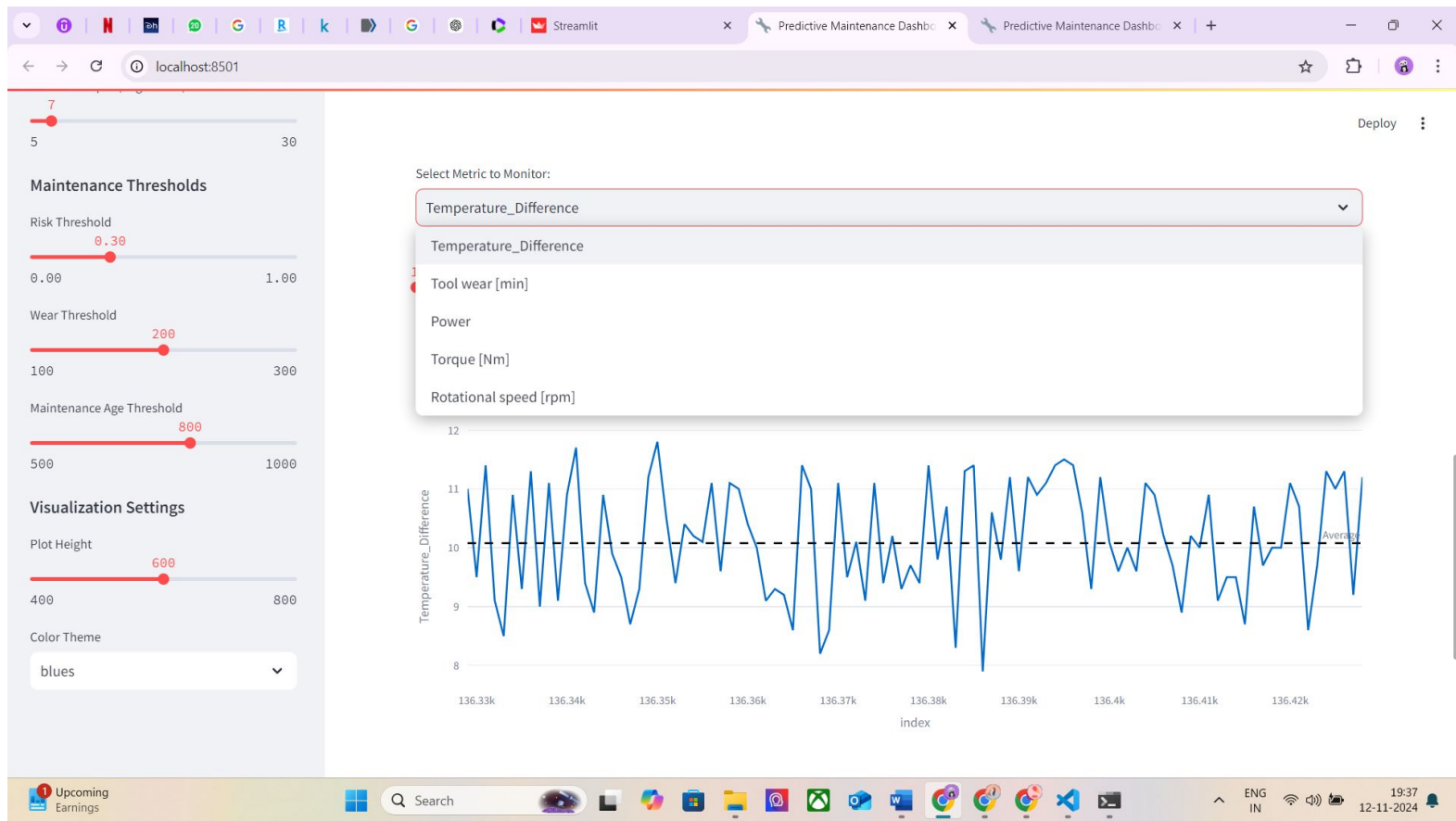
Deployment: Hosted on Hugging Face Spaces for easy access

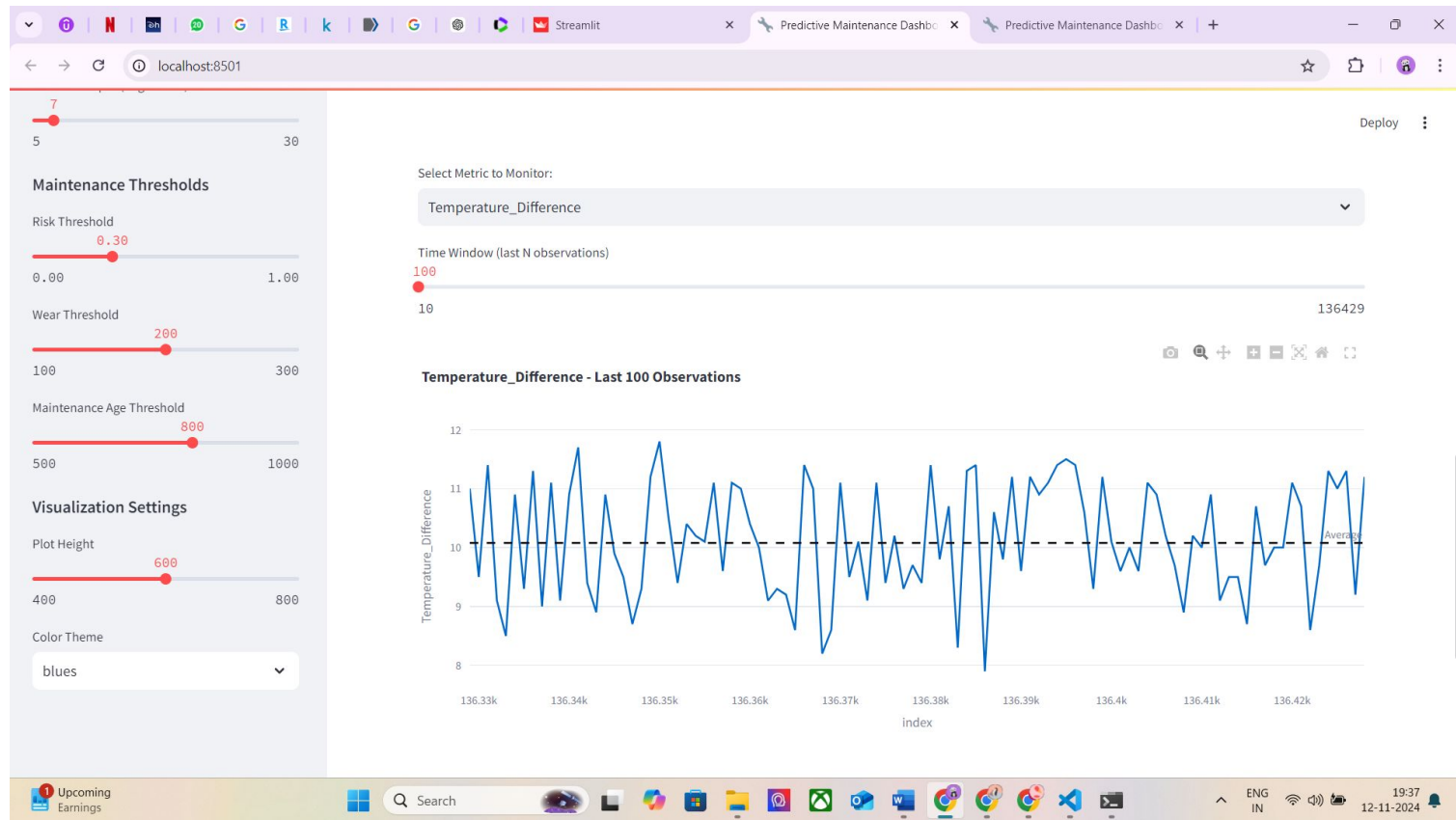
# Process Flow chart

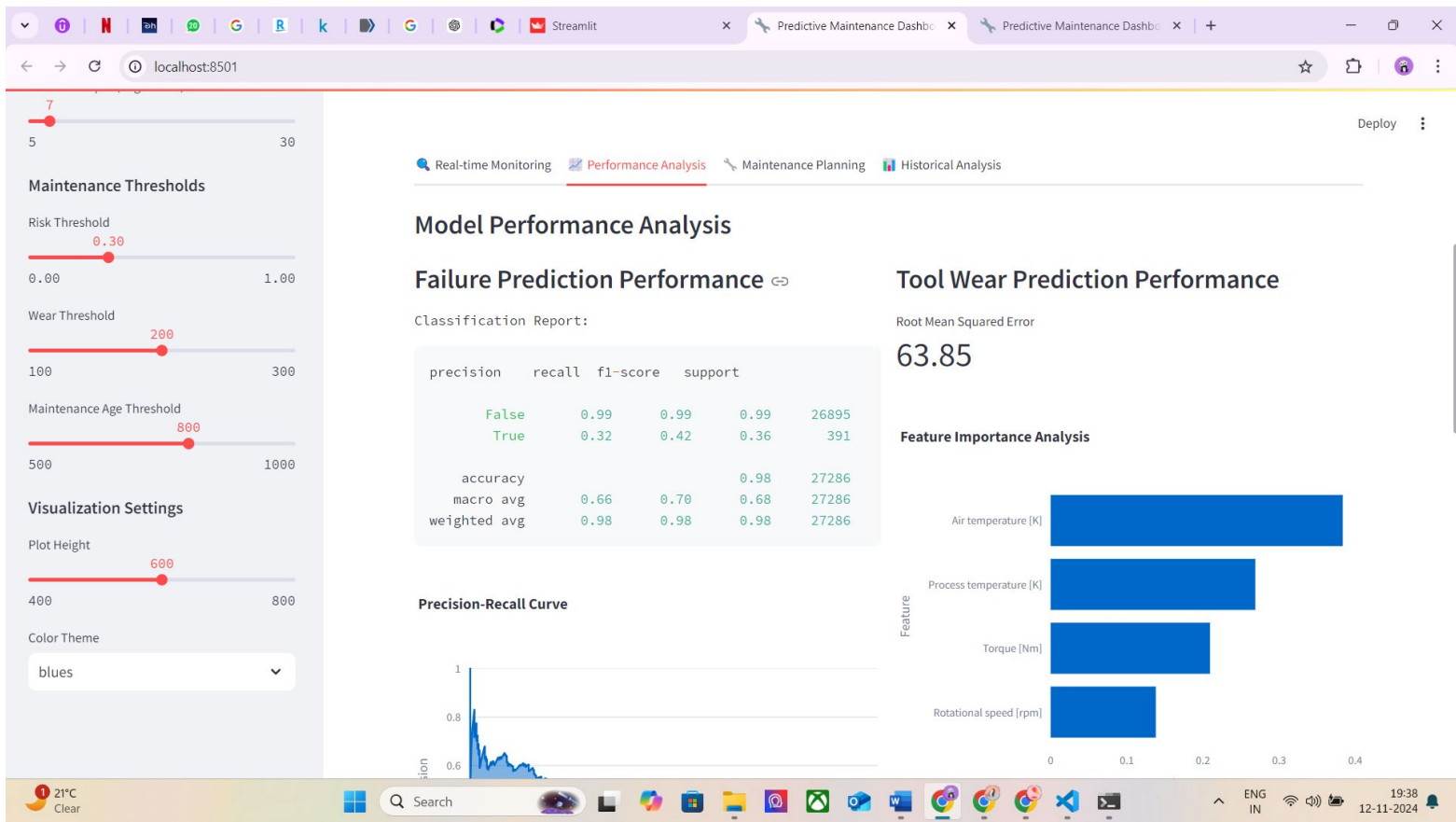


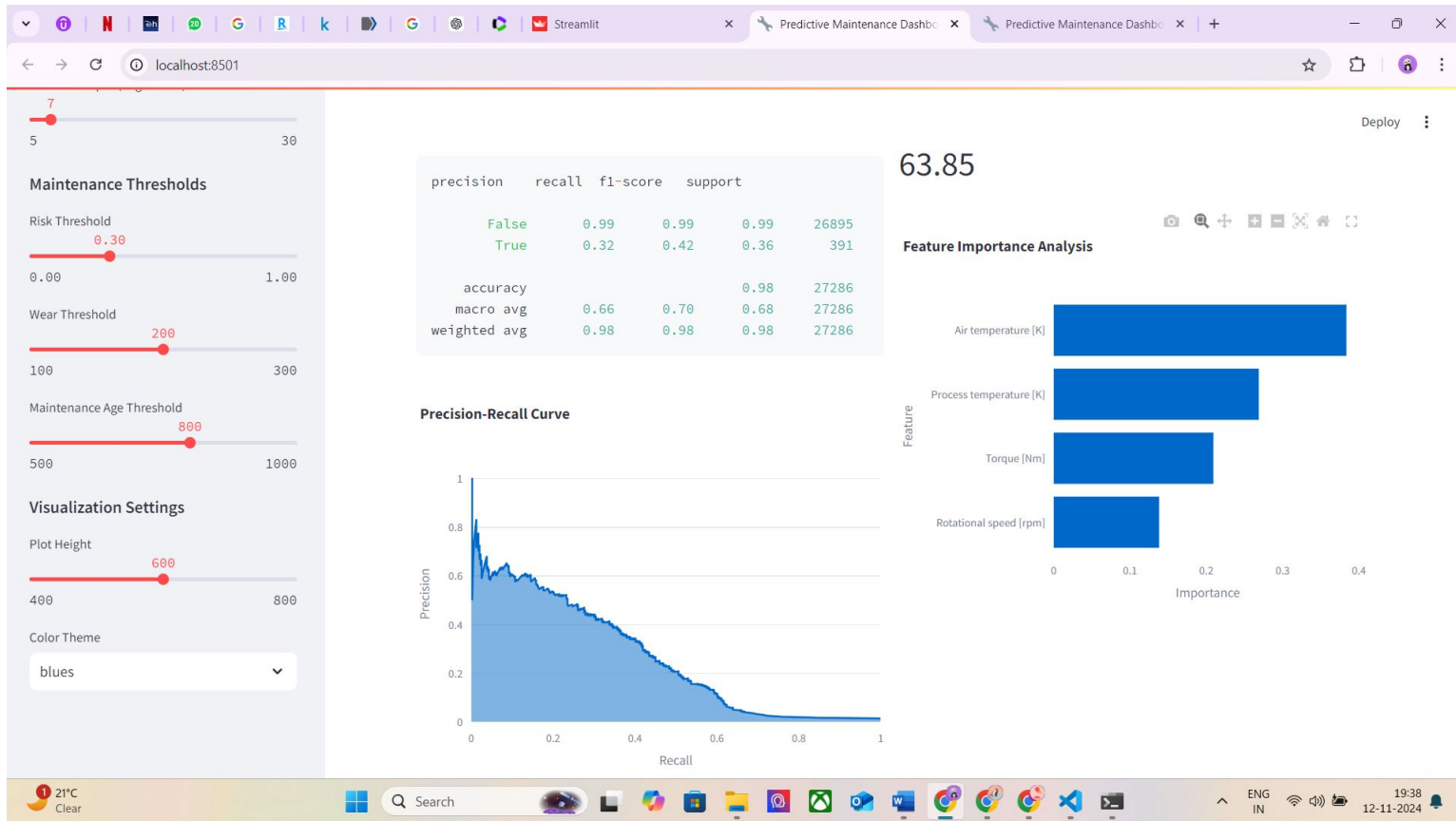






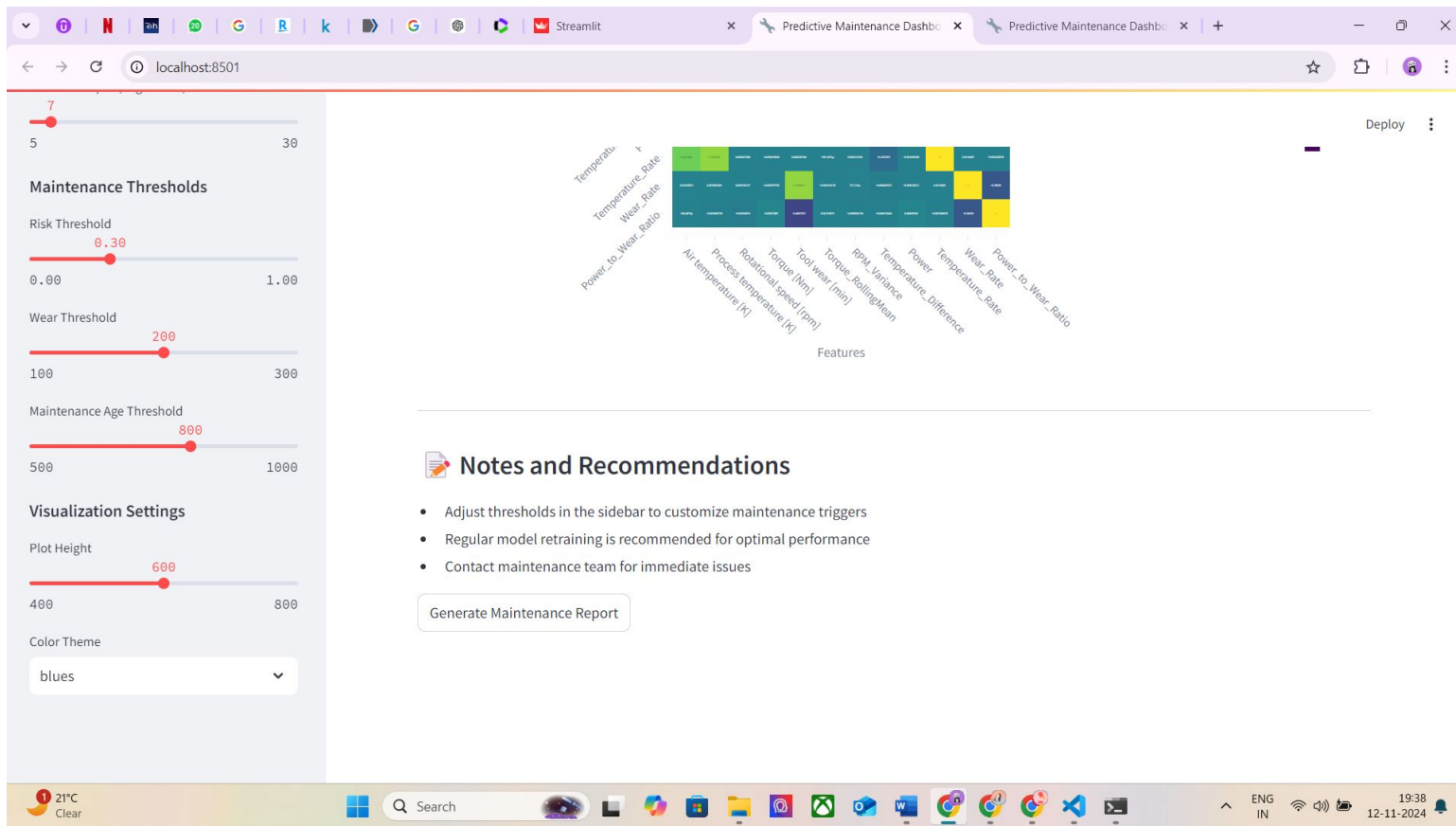


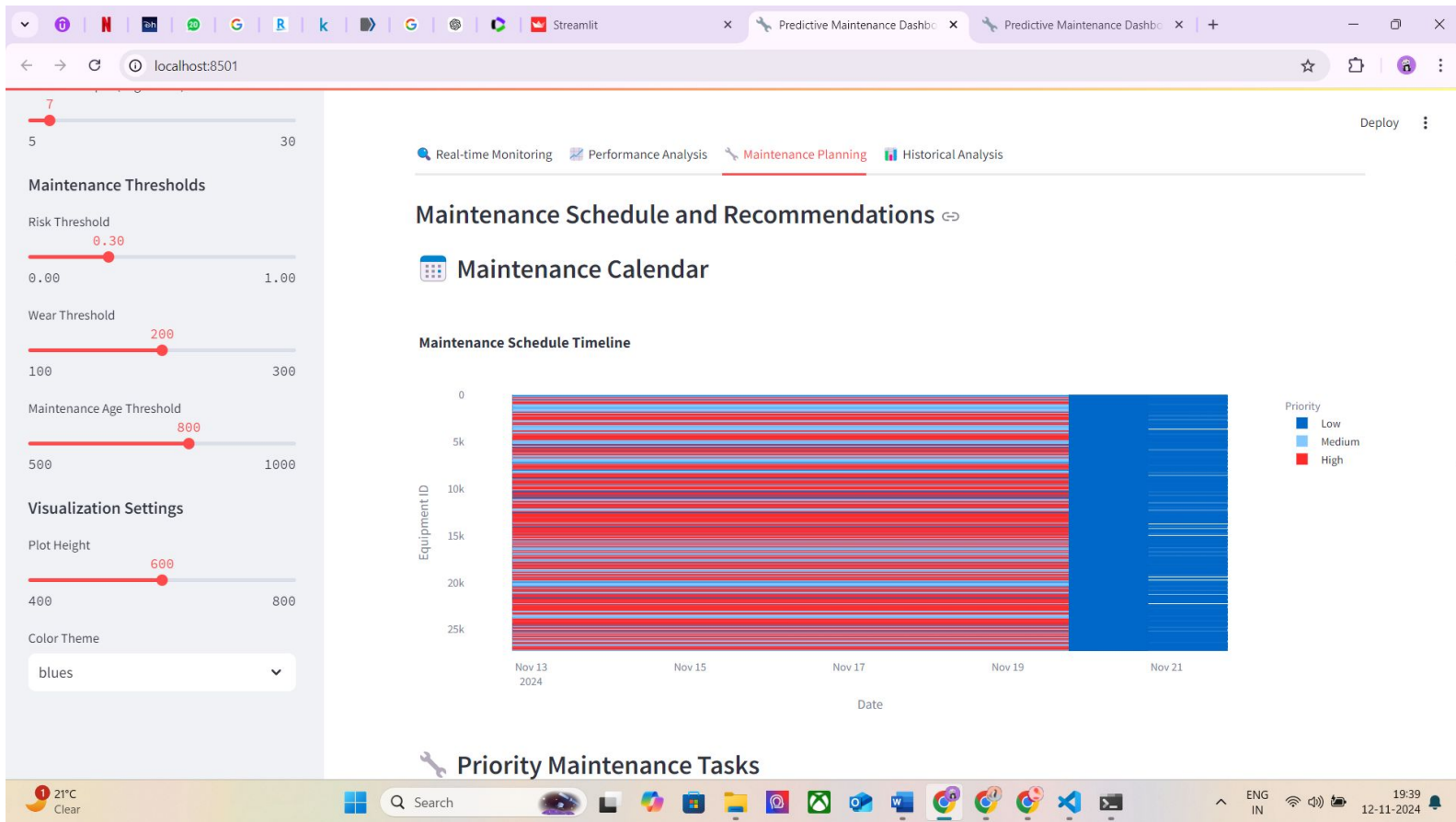


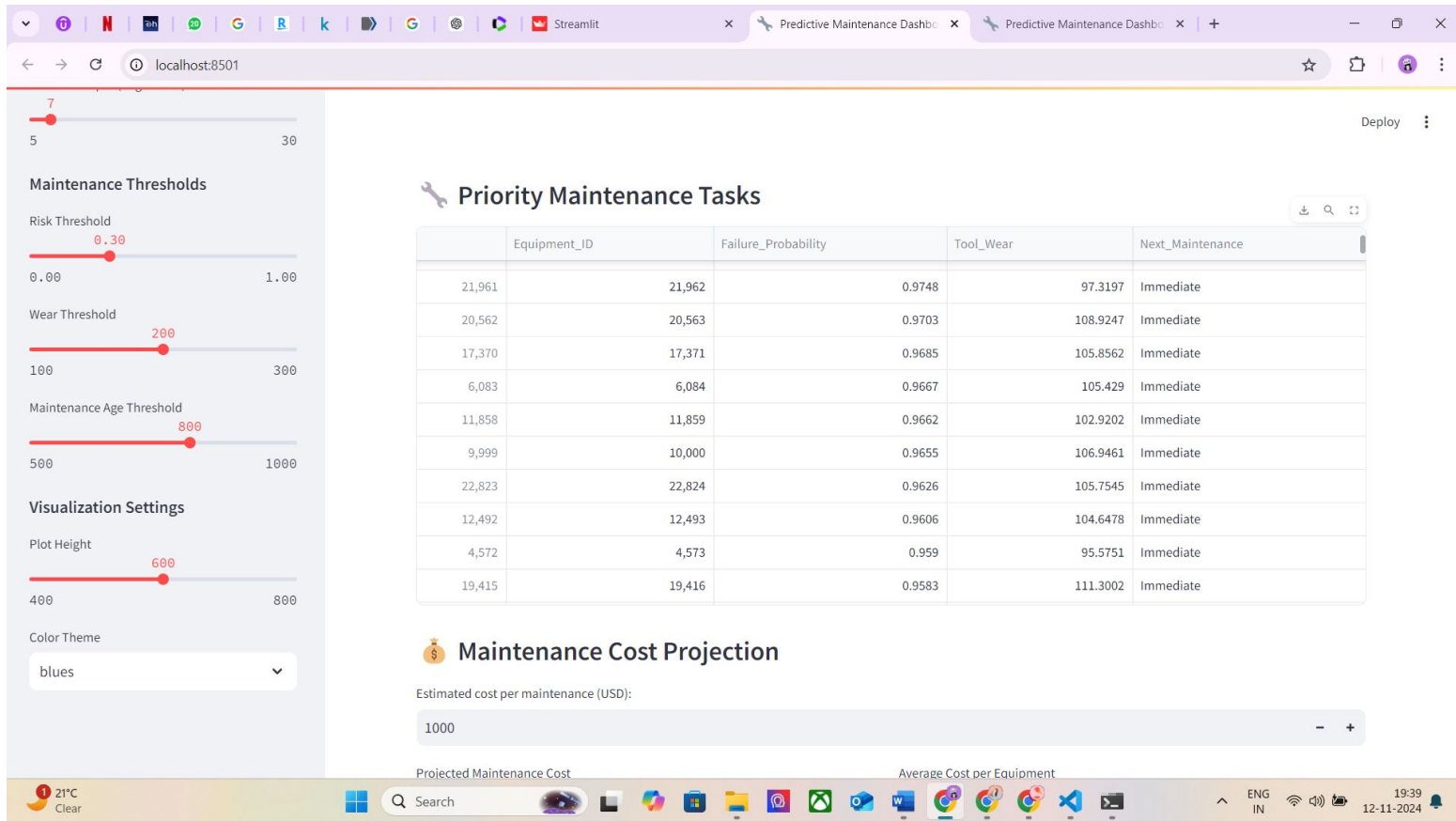












7

5

30

Maintenance Thresholds

Risk Threshold

0.30

0.00

1.00

Wear Threshold

200

100

300

Maintenance Age Threshold

800

500

1000

Visualization Settings

Plot Height

600

400

800

Color Theme

blues

Deploy

Equipment ID	Current Value	Threshold	Score	Alert Level	
EQ-001	4,572	4,573	0.959	95.5751	Immediate
EQ-002	19,415	19,416	0.9583	111.3002	Immediate

Maintenance Cost Projection

Estimated cost per maintenance (USD):

1000

Projected Maintenance Cost

Average Cost per Equipment

\$6,385,000.00

\$234.00

↑ \$6,375,000.00

Notes and Recommendations

- Adjust thresholds in the sidebar to customize maintenance triggers
- Regular model retraining is recommended for optimal performance
- Contact maintenance team for immediate issues

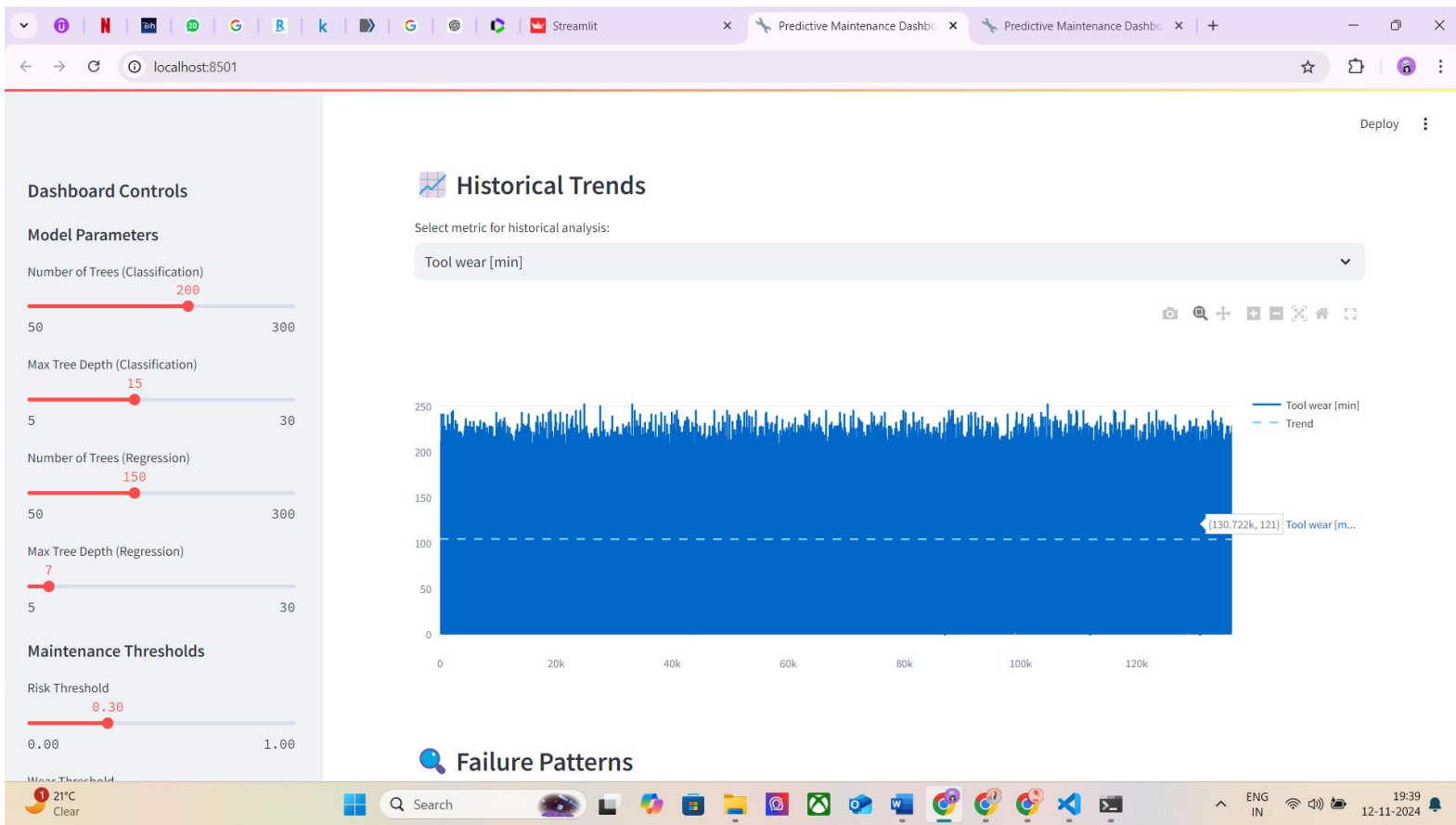
Generate Maintenance Report

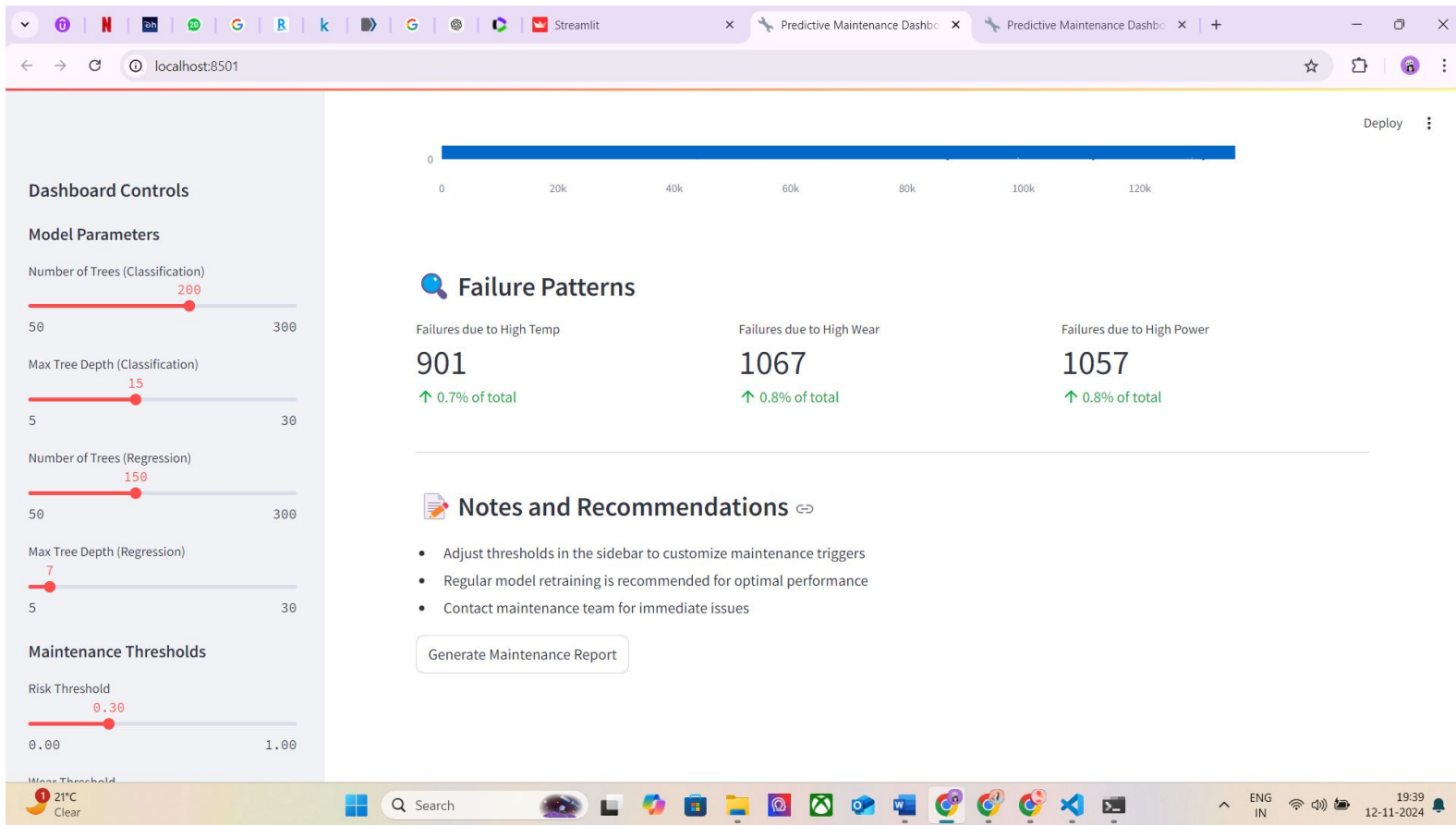
21°C Clear

Search

Taskbar Icons

System Tray





# Conclusion

## Challenges and Solutions:

1. Data Quality: This has been one of the greatest challenges as incomplete, noisy, or inconsistent data is a very common phenomenon in real-world datasets. Missing values, outliers, and irrelevant features usually arise in the real dataset.

Solution: We removed irrelevant columns from data. Normalized and scaled to standardize data. The model's performance and flexibility improved by using feature selection techniques to remove redundant features.

2. Data Preprocessing: It learned very well initially on the training data but could not generalize well to the new data and was particularly bad when the dataset is small or highly unbalanced.

Solution: Since this is a categorical feature, which is the different kinds of machines, we would need to apply label encoding or one-hot encoding to make it usable by a model in the 'Type' column. Label encoding simply assigns unique integers to each category, and one-hot encoding adds separate binary columns for each unique type.



# Conclusion

## Lessons Learnt

Documentation: Explicit setup and dependencies. This also is very useful for troubleshooting and team collaboration.

Model Interpretability: Ensuring stakeholders understand predictions is key for effective deployment.

Version Control & Virtual Environments: Version control through virtual environments and Git streamlined team collaboration and resolved environment issues.

Iterative Development: Successive refinement of the model based on feedback improved the performance dramatically.

# Conclusion

## Future Enhancements

- 1.Integration with real-time data sources (e.g., IoT sensors)
- 2.Additional algorithms for failure prediction
- 3.Custom alerts and email notifications for critical equipment maintenance and user experience.



# Thank You