Assignment-3

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- **Problem Statement:**
  - Identify significant machine parts in a manufacturing factory that are prone to get damaged in the near future.

- **ML Canvas:**
  - The ML Canvas is a tool designed to help plan and structure machine learning projects. It assists teams in defining the problem, selecting suitable data, choosing an appropriate model, and determining how to evaluate the results before developing the solution.

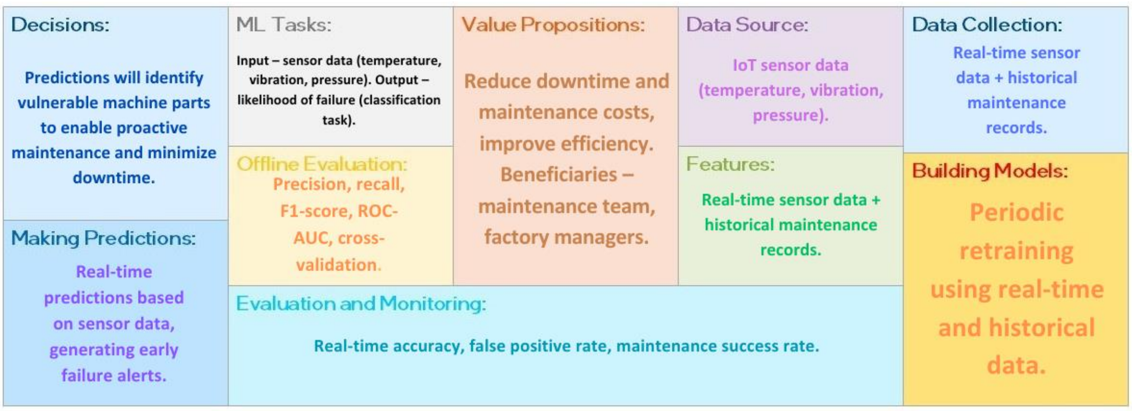

Fig. ML Canvas

- **Decisions:**
  - Predictions will be used to identify machine parts that are prone to damage before failure, allowing proactive maintenance and reducing downtime. This will improve overall efficiency, reduce repair costs, and prevent unplanned production halts. Early intervention can also extend the lifespan of critical machinery components.

- **ML Tasks:**
  - The input will be real-time sensor data such as temperature, vibration levels, pressure, and operational cycles. The output will be the likelihood of a part's failure. This is a classification problem where the model predicts whether a part is likely to fail or not. Regression can also be used to estimate the time until failure.

- **Value Propositions:**
  - The goal is to reduce machine downtime and maintenance costs by predicting failures before they occur. This will enhance operational efficiency and prevent production loss. The system will help schedule timely maintenance, ensuring smoother operations and fewer disruptions.

- **Data Source:**
  - Data will be collected from IoT-based sensors attached to machine parts, which will measure parameters such as temperature, vibration levels, pressure, and running hours. Maintenance logs and failure reports will provide additional context to improve model accuracy.

- **Data Collection:**
  - Data will be collected in real time from sensors installed on machine parts. Historical maintenance records and operator feedback will also be integrated to improve the model’s performance. Data will be stored in a central database for analysis.

- **Features:**
  - Relevant features will include temperature, vibration levels, pressure, and operational hours. Additional derived features like the rate of change of vibration and pressure trends will also be used. Environmental factors like humidity and machine load can also be included.

- **Building Models:**
    - The model will be retrained periodically using the latest sensor data and maintenance records. The retraining frequency will be determined based on the accuracy of predictions and operational requirements. Fine-tuning the model based on real-world feedback will enhance its accuracy.

- **Offline Evaluation:**
    - Metrics such as precision, recall, F1-score, and ROC-AUC will be used to evaluate the model before deployment. Cross-validation will be performed to avoid overfitting. Simulated failure scenarios will be used to assess the model's predictive strength.

- **Evaluation and Monitoring:**
    - After deployment, the model will be monitored using real-time accuracy, false positive rates, and maintenance success rates. Continuous feedback from maintenance records will help improve performance. Alerts and dashboards will enable quick decision-making and troubleshooting.

- **Making Predictions:**
    - Predictions will be made continuously in real-time based on sensor data. The system will generate alerts when a part shows early signs of failure, allowing maintenance teams to intervene before a breakdown occurs. Predictive insights will help in scheduling repairs during low production hours to minimize disruption.