## Blueprint Proposal: Predictive Maintenance of Hardware

<table>
<thead>
<tr>
<th>Case Attributes</th>
<th>Description</th>
<th>Informational</th>
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</thead>
<tbody>
<tr>
<td><strong>Type</strong></td>
<td>New Blueprint for Predictive Maintenance of Hardware at the Edge</td>
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<tr>
<td><strong>Blueprint Family - Proposed Name</strong></td>
<td>Network Cloud and computing Edge infrastructure</td>
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<tr>
<td><strong>Use Case</strong></td>
<td>Provide Predictive Maintenance of Hardware (HDD, sensors, Optics, interfaces, CPU etc) in advance before system failure</td>
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<tr>
<td><strong>Blueprint proposed Name</strong></td>
<td>Predictive Maintenance</td>
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<td><strong>Initial POD Cost (capex)</strong></td>
<td>Leverage Unicycle POD - less than $150k</td>
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<tr>
<td><strong>Scale &amp; Type</strong></td>
<td>Up to 100K devices x86/ARM server or deep edge class</td>
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<td><strong>Applications</strong></td>
<td>Our AI based Predictive Maintenance solution has application and usage in every aspect networks / data center’s / compute nodes / autonomous robots and cars.</td>
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<tr>
<td><strong>Power Restrictions</strong></td>
<td>Less than 10Kw</td>
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<td><strong>Infrastructure orchestration</strong></td>
<td>Docker 1.13.1 or above and K8s 1.10.2 or above- Container Orchestration OS - Ubuntu 22.x</td>
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<td><strong>Workload Type</strong></td>
<td>Any</td>
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<td><strong>Additional Details</strong></td>
<td>Kafka message bus and Webhook/Nginx middleware</td>
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<td>Kubeless function management engine over Kubernetes</td>
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<td></td>
<td>PMC Client with network connectivity</td>
<td></td>
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<td></td>
<td>GUI based installer for Functions</td>
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Problem Statement

- In the world of smart systems, encompassing 5G, IoT, and data centres, a critical challenge looms. These systems, designed for convenience, efficiency, and security, are susceptible to hardware, firmware, and software failures. When these failures occur, they disrupt daily operations and can lead to catastrophic consequences.

- Consider a data centre relying on hard drives as its foundation. A hard drive failure can result in data loss, operational downtime, financial losses, and damage to an organization's reputation.

- The need for proactive maintenance to prevent these failures is evident.
Solution

- Our mission commences with hard drive predictive maintenance, recognizing its centrality in data centres. However, our vision extends to encompass all smart devices, aiming to unite them under a proactive maintenance strategy.

- Our device-agnostic approach, rooted in data analysis and anomaly detection, positions us to fortify the entire smart ecosystem, ensuring reliability and efficiency at scale.

- As data centres and smart systems evolve, our model evolves with them, ensuring uninterrupted operations and mitigated risks.
Predictive Maintenance Model Generation

- Automated Testing and Training: The pipeline to automate two critical aspects of our solution: testing and training.

- Key Components of the Pipeline:
  - **Data Ingestion**: The pipeline begins by ingesting data from Backblaze along with our local data, ensuring our model is trained on the latest and most relevant data.
  - **Data Pre-processing**: It performs data cleaning, transformation, and feature engineering to prepare the data for model training.
  - **Model Training**: Our machine learning model is trained using the pre-processed data, continuously improving its predictive accuracy.
  - **Automated Testing**: The pipeline includes automated testing procedures to validate the model's performance on various datasets.
  - **Deployment**: Once the best-performing model is identified, it is deployed for real-time predictions on our servers.
Predictive Maintenance Workflow

1. Data Source → Data Ingestion
2. Data Ingestion → Data Preprocessing
3. Data Preprocessing → Model Training
4. Model Training → Model Testing
5. Model Testing → Trained Model
6. Trained Model → Prediction Analysis
7. Prediction Analysis → Third Party Integration
8. Third Party Integration → UI
Hard Disk Failure Prediction Analysis

• We focus on key SMART attributes like – SMART 5, SMART 187, SMART 188, SMART 197, SMART 198 etc. These attributes are crucial in predicting hard drive failures

• Examples of some of the Attribute Significance:
  - **SMART 5 (Reallocated Sectors Count)**: Indicates the number of sectors that have been reallocated due to errors. A rising count may signal impending failure.
  - **SMART 187 (Reported Uncorrectable Errors)**: High values here indicate the drive's inability to correct errors, which can lead to data loss.
  - **SMART 188 (Command Timeout)**: Frequent timeouts can suggest problems with the drive's response times.
  - **SMART 197 (Current Pending Sector Count)**: A high count implies sectors waiting to be remapped, often indicative of drive problems.
  - **SMART 198 (Uncorrectable Sector Count)**: Increasing values signify sectors that can't be read or corrected, posing a risk to data integrity.
Predictive Maintenance Dashboard
Next Steps

• Expand predictive maintenance platform to all smart devices and IoT devices
• Extend to LED/CPU/Memory/Network modules.
• Local log data analysis: Analysing logs generated by software systems directly on the edge device to identify patterns and anomalies indicating potential failures
• Integration of ETSI API’s
Thanks