Capstone Project Proposal

Prathamesh Morde

Business Goals

Introduction:
I will be focusing on telecommunication or communication service providers (CSP) industry.

Project Overview and Goal What is the industry problem you are trying to solve? Why use ML/AI in solving this task? Be as specific as you can when describing how ML/AI can provide value. For example, if you're labeling images, how will this help the business?	**Current Problem –** Today there are around 1 billion IoT devices connected to networks are too much for management systems to handle. This number expected to increase in upcoming years. It is impossible to provision, activate, monitor and assure devices at great scale manually. The daunting challenge of managing the infrastructure and business processes necessary to optimize performance and monetization. **Goal –** The goal is to develop an intelligent fault prediction, detection and correction network that will transform how network services delivered. Today CSPs collect huge amounts of network and customer data. The AI, Machine learning and deep learning approach is proposed which will bring following business values 1. Ability to self-configuring, self-healing, self-optimizing and self-evolving network infrastructure. 2. Ability to configure zero-touch services. 3. Best possible user-experience.
Business Case Why is this an important problem to solve? Make a case for building this product in terms of its impact on recurring revenue, market share, customer happiness and/or other drivers of business success.	**Why it is important** As per [Ericsson mobility report] 2.6 billion 5G subscribers will be generating 65% of the world's 160 exabytes of mobile data traffic per month within five years. The large number of devices and high network complexity lead to a higher chance of link faults. The link faults lead to service degradation and increase repair time.

	Outcome - With the help of AI automation CSPs will not only help reduce manual, time consuming tasks but will also increase the operational efficiency and improve customer experience.
Application of ML/AI What precise task will you use ML/AI to accomplish? What business outcome or objective will you achieve?	We will apply a machine learning and deep learning model to identify fault events in the network and process the correct action based on the type of fault. The model will detect/monitor the network faults. We will achieve this with the help of four stages 1. Detect if a fault has occurred or not. 2. If a fault has occurred, then it will analyze whether it is real fault or not. 3. When the model will fix the fault then it will send the metrics (troubleshooting workflow) to the network administrator. 4. If the model won't able to take an action, then it will network admins to perform the necessary steps.

Success Metrics

Success Metrics What business metrics will you apply to determine the success of your product? Good metrics are clearly defined and easily measurable. Specify how you will establish a baseline value to provide a point of comparison.	Mean time to restore/recovery – Time taken by the model to fix a downtime incident. Mean time to resolution – Time required to fix the problem and implement subsequent steps to keep the problem from recurring. Having less mean time to recovery and resolution will help to increase the operational efficiency and improve customer experience.

Data

<table>
<tr><td>Data Acquisition

Where will you source your data from? What is the cost to acquire these data? Are there any personally identifying information (PII) or data sensitivity issues you will need to overcome? Will data become available on an ongoing basis, or will you acquire a large batch of data that will need to be refreshed?</td><td>Source of Data –
There are different ways we can source the data.

1. We can leverage data from network database systems.
2. We can collect and parse operational and configurational live data from network devices using different networking protocols (For example SNMP, NETCONF etc.)

Cost to get Data –
The cost to acquire data would be higher because we will be pulling data from the devices (different vendors) for better predictions. It is possible we need to spend some capital to develop certain monitoring applications which will help us to feed the data to the ML-based Fault model or manager.

Data sensitivity -
Since we need to monitor the health of the network, we need to mask sensitive information such as user's personal details, browsing history, IP addresses, exchanging private information with vendors and between vendors.

Data availability -
Data will become available on an ongoing basis since we can collect the network data daily so there will be no need to get a large batch of data.</td></tr>
<tr><td>Data Source

Consider the size and source of your data; what biases are built into the data and how might the data be improved?</td><td>When training a model is to train with all types of data its best to consider all types of scenarios. We will start with a few hundred examples of each data class and then scale up until we find the desired accuracy.

The networks in the production field spits out Terabytes of data. To support that we need to feed lots of data to gain the confidence level.

The sources of data categorized into:
- Alarms (Provides information of the severity of the problem)
- Network congestion failure (Packet loss)
- Hardware failures (Cable fault)
- Software failures (Defect in software release)

The biases built into
1. Annotation bias due to human handling in the process.
2. ML model bias due to bias generated by model outcome.</td></tr>
<tr><td>Choice of Data Labels</td><td>Based on the sources of data we will be using following data</td></tr>
</table>

What labels did you decide to add to your data? And why did you decide on these labels versus any other option?	labels 1. normal_operation 2. hardware_failure 3. software_failure 4. congestion_failure 5. alarms_failure **Strengths -** This data labelled technique will help to distinguish between normal operation and each type of fault. It will provide a much richer source of fault data. **Weakness –** • There would be possibility of mislabeled, dirty data which can impact the model performance. • We are collecting data from different vendors/devices and each will spit out different types of fault scenarios thus the model may not able to generalize to best performance when faced with the new data. • Not having enough data (uneven distribution) would lead to a bias model.

Model

<table>
<tr>
<td>Model Building

How will you resource building the model that you need? Will you outsource model training and/or hosting to an external platform, or will you build the model using an in-house team, and why?</td>
<td>For fault management systems there are couple of out of the box ML models used often to handle a range of issues rather than crafting your own model to address one specific problem.
ML model which we could leverage
- Supervised/Unsupervised analytic model (Used for detection, diagnosis and root cause analysis)</td>
</tr>
<tr>
<td>Evaluating Results

Which model performance metrics are appropriate to measure the success of your model? What level of performance is required?</td>
<td>For model’s performance following metrics would help to measure the success of the model

<table>
<tr><td>Metric</td><td>Definition</td></tr>
<tr><td>Accuracy</td><td>Number of correct predictions the model got it</td></tr>
<tr><td>Precision</td><td>How much the model able to categorize into a specific</td></tr>
</table>
</td>
</tr>
</table>

	label
Recall	Relevant results correctly classified by the model
F1 score	To find the balance between precision and recall.
Confusion matrix	To identify model’s biasness and where model is failing.
Sensitivity	Ability to tolerate noisy or missing data.
Response time	Time to complete detection, diagnosis and perform root cause analysis

In order to achieve the success metrics, the model able to detect faster and able to take an action effectively.

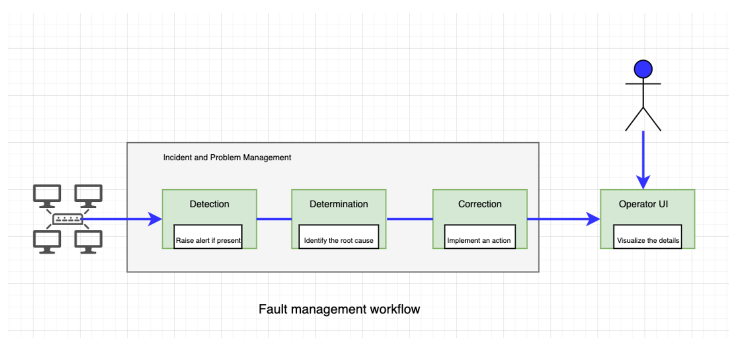
Minimum Viable Product (MVP)

Design

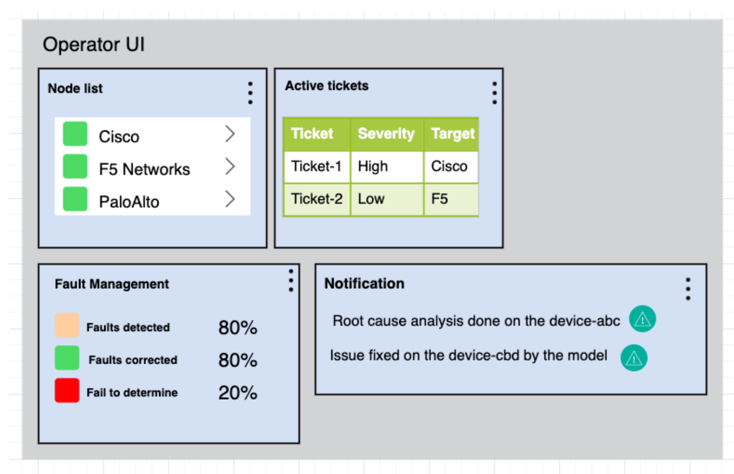
What does your minimum viable product look like? Include sketches of your product.

The outcome of MVP will cover following things –

- Ability to detect faults (alarms, network congestion failure, hardware failure, software failure)
- Ability to visualize the number of faults captured, resolved and also notify operator about a root cause analysis.
- Send a notification to operators when the model won’t able to take an action (Trigger a ticket)



<table>
<tr>
<td></td>
<td>



</td>
</tr>
<tr>
<td>

Use Cases

What persona are you designing for? Can you describe the major epic-level use cases your product addresses? How will users access this product?

</td>
<td>

Persona Example-1: Roger Knight

- 32 years old
- Network operator/admin
- Master's in computer engineering
- Major believer in customer experience improvement.

Roger's pain points

- Frustrated by manual steps to perform when there is a network outage
- Concerned that his customers are being affected because time it takes to resolve an incident.

Persona Example-2: Minna Lang

- 31 years old
- Network Architect
- Master's in computer science
- Major believer in innovation.

Minna's pain points

- With 5Gs anticipated IoT explosion, manual detection, correction won't able to support low latency, high bandwidth requirements.

Use Case:
As networks become more complex and software driven there is an urgent need to use more proactive methods for addressing service disruptions.
To address this challenge, an AI fault detection model not only predict but also proactively outages which in turn improves the customer experience, reduces manual intervention, increases operating efficiency.

Customers able access product with the operator UI. This UI will help them to understand

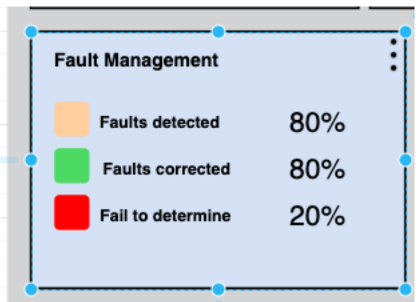
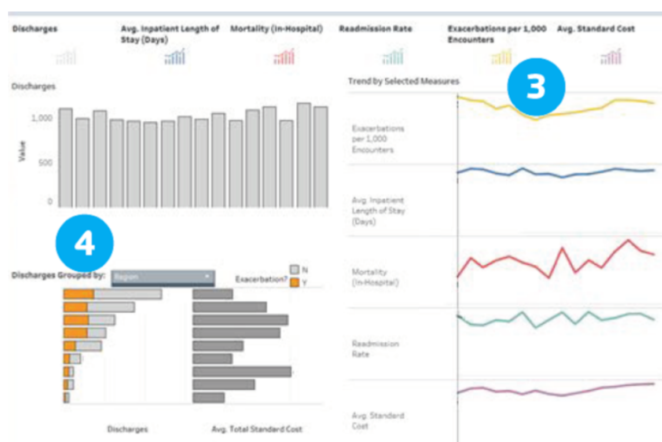
- The list of devices monitored, device information,

</td>
</tr>
</table>

	health. - Number of times faults detected, corrected. - Active tickets operator needs to work on when model fails to correct the issue. - Network operators, admins or architects will also see the notification about the root cause analysis performed by the model.
Roll-out How will this be adopted? What does the go-to-market plan look like?	**Product Adoption-** By deploying in the customer's lab environment for field trials. 1. Validate with the data engineering team to ensure security compliance with the product. 2. Align with the sales team to ensure that leaders are aware of product rollout. 3. Communicate with stakeholders and get an alignment on the expected rollout dates. 4. Before actual production rollout the model will go through tests and the model's performance metrics, customer feedback measured and tweaked. 5. Once all the necessary tests and bugs fixed then the product would be deployed in client's production environment.

Post-MVP-Deployment

Designing for Longevity How might you improve your product in the long-term? How might real-world data be different from the training data? How will your product learn from new data? How might you employ A/B testing to improve your product?	**Product Improvement -** - Product feedback from customers and adopting in the new release. - Refreshing and updating the model with the new data to remove model staleness. In the current design when the model could not able to take an action (non-confident data) then it will create a ticket so the human will take a look and fix the problem. In order to improve the learning process in the future release the human able to feed that information back to the model. There are numerous faults type occur in the networks and feeding the new information back to the model will have a higher confidence level than before. The real-world data is different from training data -> - Training data is used by model to find the patterns that distinguish different types of classes. The model learns from this data - RWD obtained from real world sources/scenarios.

	RWD are collected and stored in a variety of source to be later analyzed alongside similar data that may provide new insights about data or network faults. **A/B testing –** **Operator UI -** Under fault management tab we are showing only percentage figures for faults.  For A/B testing we can show statistical graphics to provide more detailed fault information.  [Reference]() **The model –** We can deploy another model along with analytic model. The active technique which is based on the reinforcement learning. After deploying two different models compare the performance metrics after which a decision can be made on the winning model.
Monitor Bias	In order to mitigate unwanted biases – 1. Refreshing and updating the model with the new data.

How do you plan to monitor or mitigate unwanted bias in your model?	2. Making sure that model’s performance metrics (specified under model section) are continuously monitored and corrected. 3. Choosing the right model for the problem. 4. Diversify training data.