Capstone Project Proposal

Mario Sorgente

Business Goals

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?	This product is a software platform capable of monitoring the asset integrity of structures and heavy assets operating in harsh environments. The platform can assess and report inspections and condition monitoring challenges via structural analysis. Data streamed via sensors are collected and analyzed via the software that will provide: **Output:** • Signals parameters • Signals categorization • Threshold trigger for human action **Outcome:** • Efficiency • Return of Investment • Safety The ML/AI is useful to correctly distinguish different types of failures in the structure, autonomously, without engaging inspectors (time and money consuming). Providing for each case the correct counteraction to prevent/fix a more severe failure. The platform needs to be trained on different applications and expected signals. For instance, a typical algorithm could be: • Monitoring the structural cracks, deflagration, deformation etc. via Acoustic Emission techniques and collecting the data via the sensors. • Classifying based on image the different failures (is it a crack? Is it a deformation?) • Output the parameter and the classification to help the engineers decide corrective actions and

	the business avoid expensive costs • Automated report

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.
	The business case is valid for three main points:
	• Efficiency
	  ○ No need to engage inspectors to monitor the asset. Making the inspection process more efficient and repeatable than manual alternatives
	• Return of Investment
	  ○ Depending on the asset to be inspected, the ROI is fundamental for both reducing the shut-down costs and to save the equivalent of x days of work (man hours). Result saving are significant, as downtime for e.g. refinery process unit can cost hundreds of thousands of dollars per day
	• Safety
	  ○ With a reasonable amount of quality data, the safety is improved because the decision is not dedicated to one inspector only but on a plethora of professionals in the structural monitoring field
	
	From the company point of view, developing such platform will affect positively:
	• The revenue: having an online platform a possible engagement could be selling a fixed fee to install and setup the software and a monthly fee to keep the data collection and analysis continuous. This will help the company to have a continuous revenue stream
	• SHM and asset integrity market is in expansion, due to many failures in big structures in the recent years. Both governmental and private companies are running tenders, plans and investments in the upcoming year to find solutions to this problem. Every hardware must be coupled with the correct software since the data analysis is one of the challenges in this market and it is tricky to get clean data (thus ML model training here is key)
	• Customer satisfaction relies in a holistic approach, where combining hardware, software, data processing results in a deterministic action to fix or not a flagged input. Since the data-process is the most challenging part, the ML platform will help analyzing as much as cases studies in real world to provide the most efficient,

	effective, cost saving, action

Application of ML/AI
 	
What precise task will you use ML/AI to accomplish? What business outcome or objective will you achieve?
	The platform can be tailored on different applications and diverse signals to be analyzed. Put in simple terms, an image categorization model with high precision is what we want to achieve here.
	
	Tailoring the product on the acoustic emission NDT, data are collected through the platform. Acoustic emission signal pictures are showed and categorized extracting the parameter associated to each category. E.g.
	• Platform acquires AE_signal1
	• Model detects the nature of the signals among the categories below:
	  ○ Crack (transversal, shear)
	  ○ Deflagration
	  ○ Fiber Debonding
	  ○ Deformation
	  ○ Metal Blistering
	• Model outputs:
	  ○ The exact failure with the acoustic emission parameters
	  ○ The severity (light traffic) and the deterministic action to fix the failure
	• Model outcomes
	  ○ Efficiency (no inspector needed, no lag time between decision, no biased decision from one inspector only)
	  ○ ROI
	  ○ No shut down costs

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.
	• User adoption and retention
	  ○ With the monthly fee approach, you can check how many companies continue using the platform
	  ○ NPS: net promoter score
	• HITL (human in the loop). Periodic check with Inspector annotators to understand the platform performances. Collaboration with universities can help also in this, engaging PhD students to annotate and provide a score 1-5 on the platform outputs

Data

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?	Data acquisition and training is key here. Provided that no company name, assets and types of analysis are shared, there are not many concerns in terms of data privacy, showing only signals. Data acquisition: • Application Definition • Collaboration with Universities and Research institutes collecting signals in lab environments. Data bought in batch with tests and data annotation • Collaboration with sensor companies collecting signals in real-world situation. Buying data in batch or collaborating on long-term projects via tenders/government funding • The more the application is tailored, the more the data need to be refreshed
Data Source Consider the size and source of your data; what biases are built into the data and how might the data be improved?	• Storage challenges from dealing with huge volumes of data. • Network challenges because you want your model to perform. • Compute challenges because you need really powerful infrastructure to run your models.

	To help with all of these challenges, well-defined machine architecture is key. The bias can arise from: • Data annotation HITL→ it is important to diversify the professionals involved in this task. Inspectors from different field with high • Unbalanced data during training sessions. Once the image are correctly labeled, you need to provide to the model the same amount of signals for each category Data can be improved involving high skills professional in data streaming and annotation. Experience on the field, getting feedback from asset companies is also fundamental.
Choice of Data Labels What labels did you decide to add to your data? And why did you decide on these labels versus any other option?	○ Crack (transversal, shear) ○ Deflagration ○ Fiber Debonding ○ Deformation ○ Metal Blistering The above are most of the failures that can be easily detected from a passive acoustic emission NDT

Model

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?	For a prototype, it is possible to start using Google cloud AutoML vision. Not having many restrictions on the privacy, for the very first batch of data we can start having an idea on the platform. As second and immediate step, it is fundamental to develop an in-house team composed of: • Product Manager • Head of Technology • Designer • Data Scientist • Consultant (inspectors) With the help of an in-house team, the platform can be way more flexible and can be tweaked in every details.

	After all, the details represent the threshold to identify one category, or another.
Evaluating Results Which model performance metrics are appropriate to measure the success of your model? What level of performance is required?	Accuracy is important but it is not the key. I would focus on high precision. Precision tells us, from all the test examples that were assigned a label, how many actually were supposed to be categorized with that label. This means be very effective in categorizing every acoustic signal in the correct corresponding failure. Safety parameter cannot be sacrificed, precision>97% is needed. In the worst case of a misprediction, a deterministic action will be anyway suggested from the platform. This means that the failure will not be overlooked.

Minimum Viable Product (MVP)

Design What does your minimum viable product look like? Include sketches of your product.	Please see sketch figure 1 below. The depicted MVP collects the annotated data and outputs the type of category with signals parameters, severity and deterministic action.
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?	B2B. User persona are: • Asset Managers/Innovation Managers/Project Managers • Looking for a solution to reduce the shut-down cost for their asset, keeping high level of safety and accuracy in the results • Looking for a way to interpret the plethora of data they gather from their inspection equipment, moving forward to a fast deterministic failure fix Major epic-level: monitoring assets in harsh environment condition, providing a “light-traffic” approach on the failure severity and consequent action. Users access the products via cloud, opening the platform with all the data sourced.

Roll-out How will this be adopted? What does the go-to-market plan look like?	Using the product-market pyramid method: **Target Customer** • Check existing customer • Interview KOL • Talk to Marketing, R&D, PMs • Firmographic Segmentation **Define underserved needs to develop VPs** • Usually, universities needs are different from industry ones • Are the customers happy with existing solution to the problem? • Do competitors appear to be successful in delivering these solutions? • Is the price that competitors charge appropriate? • What new benefits would the product deliver? (Aside from being cheaper) **Value Proposition Iteration** • Unique Selling Point definition • Urgency of need • Worth to customer • Market size • Competition • Time to Market

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?	Data longevity and refresh is very important here. Long term, the more the application gets tailored, the more the signals must be specific with detailed action point to take, considering the severity. • Refresh data with projects/tenders/collaborations with private companies, research institutes and governments • Real-world data are very different since usually they are immersed in noise. Noise level plays a fundamental role and the distinction between noise, artefact or relevant signal is key in data interpretation. Feeding the model with real world data is vital part of reiteration process • The categorization of a new application and consequently new labels is the way the model can learn from new data • A/B testing could be helpful via using image categorization vs video categorization using

	machine vision. After all, the real inspection is conducted with inspector “visual inspection”. The new model could be based on videos and not on images. However, it is necessary to run some business tests to understand whether the complexity of the new algorithm is worth the ROI
Monitor Bias How do you plan to monitor or mitigate unwanted bias in your model?	There are several ways to mitigate bias, including collecting data from multiple sources and not relying too heavily on academic data. It is also helpful to cover the maximum number of edge cases and scenarios and test with all of your end-users. Lastly, having a diverse set of teams and groups working on your data can help highlight potential problems.

Figure 1 – Sketch UI