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| Capstone Project Proposal |  |

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**Business Goals**

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| **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? | The problem is to help a car manufacturing company detects defect in their engine production parts. ML/AL would help the company annotate the defects and non-defect pictures(images) quicker than the time required for human to manually label the defect pictures(images) of the engine parts. |
| **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 problem of having unhappy customers returning defect machine parts has impacted the sales of cars seeing a drop of 30% in sales in the last quarter of 2020. To resolve these problems of unhappy customer and fall in sales we shall attempted to apply ML/AI to support the labelling and prediction of defect engine parts. |
| **Application of ML/AI**  What precise task will you use ML/AI to accomplish? What business outcome or objective will you achieve? | The Main tasks of the ML/AI is to help with   * Flag defect engine parts from production line images * Flag quickly non-defect engine parts * Help as a detecting aid for Engine production engineers. For this task a classification model will resolve the problem of Engine parts defects. |

**Success Metrics**

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| **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. | The Success metrics would be   * Better and faster decision making on defect engine detection * Reduction of defect engine recall * Better customer experience * Increase sales and revenue gain   The baseline will be set base on existing estimated of sales per year, revenue per year, customer NP scores, customer retention rates. This would be an iterative process, by monitoring and revisiting the success metrics to ensure if there is increase in performance of these success metrics against the benchmark. For example, if label images has low confidence it would be pass to human to annotate the image and this would be passed back to the model. |

**Data**

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| **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? | The organization currently have historical data sufficient to carry out a classification model problem and does not need additional cost of acquisition of images. The project does not directly have PII datasets or sensitive customer data. They have ongoing high definition camera on production line that capture engine part images are pulled into a database.  The batch of data would be refresh with built in processes to handle identified and defined issues to mitigate against any data privacy concerns in relation to customer PII |
| **Data Source**  Consider the size and source of your data; what biases are built into the data and how might the data be improved? | Considering the historical data in the organization, it is likely to have imbalance data labels for defect and non-defect image labels(data bias), human ideological bias(annotation bias) for hand label images and also a model bias introduced by the model itself. If not, appropriately address could be bad for the business and customers. Built processes to handle unwanted bias through awareness, defining the problem and details the model wants to solve; from the source of data, in the train and apply same to test datasets, subject matter expertise will also be apply to help in continuous improving our data. |
| **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? | There are two labels (binary problem): one captures non-defect images and the other capture defect images of engine parts. A binary classification problem. The reason been that an image could capture multiple cracks and another without cracks. |

**Model**

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| **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? | The project would be resource by existing in-house team as that is the decision of management and subject matter expert/customers. The development and dev op team will be responsible for hosting and operationalizing the model. |
| **Evaluating Results**  Which model performance metrics are appropriate to measure the success of your model? What level of performance is required? | The confusion matrix is commonly used to evaluate binary classification model such as this one. Precision and recall give us a clear picture of what is actual points and predicted points of the classification model. F1-score and accuracy would also be used to check the performance of the model. A recall and precision closer to 1 will be a good model than the one closer to 0. F1-score will be set to 0.5 |

**Minimum Viable Product (MVP)**

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| **Design**  What does your minimum viable product look like? Include sketches of your product. | The plan is to build a binary classification machine learning solution that would help a car manufacturing company identify defects and non-defect engine parts in a timely manner to improve profit and customer satisfaction. This will involve defining the problem, collect data, instructing the developers/data scientist on the MVP specifications, prep and transformation, select and train model, deploy model, use model to make decision or prediction, evaluate product performance    Type of ML description Example  Classification pick N labels Defect or non-defect |
| **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? | The Senior management, internal stakeholders, and external customer of the business. The binary classification model will help address and support business as usual address defect machine parts in production in a more agile way to resolve these defects as quick as possible in real time. As this will be deployed into production lines for the ML/AI could sort defects in real time with little human intervention saving cost and customer satisfactions |
| **Roll-out**  How will this be adopted? What does the go-to-market plan look like? | The Dev Ops and ICT will be responsible to roll-out the product into production. The output will be available to Production manager in a dashboard for to enable live decision making. |

**Post-MVP-Deployment**

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| **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? | Live data will be feed into our model, labels with low confidence level, novelty, etc will be pass to human for re-processing and feedback into the model. Another strategy is to build A/B testing. A challenger model that measure against the chief model to check for performance of the chief model, by feeding 20% of the images into the challenger model and 80% into the chief model and check which performed better. |
| **Monitor Bias**  How do you plan to monitor or mitigate unwanted bias in your model? | Through identification of the unwanted bias, build automated anti-bias algorithm to monitor bias from the source and continuous monitoring of confusion matric for the model bias. The risk will be pass to the DevOps team to monitor bias of the model. |