Capstone Project Proposal

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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?	Artificial Intelligence/machine learning (ML/AI) has been adopted for addressing complex issues that necessitate a high level of human intelligence, particularly in the health industry. One of the most important applications of ML/AI in the medical industries is the field radiology. Therefore the industrial problem we are trying to solve is diagnosing brain tumors in magnetic resonance (MR) images. We want to build ML/AI application that will take in MR images and automatically tell us if the image contain tumors or not. Therefore in this project, we want focused on combining AI and radiomics to diagnose brain tumors in patients at different levels.
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.	Detecting tumors in radiographic images is a major concern in the health sector, but it is a complicated and time-consuming process that radiologists must undertake, while the accuracy of their findings is solely dependent on their expertise. Most of the today's radiology diagnoses, such as magnetic resonance (MR) examinations, are primarily based on personal judgment and may be insufficiently accurate and the risk that patients encounter may be very high. Therefore, leveraging Artificial Intelligence (AI) technology in order to reduce the inaccuracies in the diagnosing process is vital. In 2020, only 150,075 patients with brain tumors were able to be identified, out of which 10,321 lost their lives before they were identified as tumor patients, according to the world health organization's annual report. Therefore, based on this report, the health sector lost millions of dollars in this process because these lives could have been saved using this ML/Al application and it could generate a lot of revenue for the health

	industry. Because, rather than radiologists spending hours trying to diagnose a single patient using MR images, this application can diagnose thousands of patients in 2 minutes with a high level of accuracy, bringing smiles to the faces of health-care workers. This application in the health care market is simply expected to grow exponentially within the next five years; it's expected to reach around 45 to 50 billion U.S. dollars by 2026 from the current evaluation of 25 billion U.S dollars.
Application of ML/AI What precise task will you use ML/AI to accomplish? What business outcome or objective will you achieve?	We will use ML/AI to diagnose a huge number of patients with brain tumors using MR images in a very minimal time frame with a high level of accuracy, which could take human intelligence days to accomplish with a low level of accuracy. The business outcome we are trying to achieve is to generate high revenue by diagnosing many people at a time, because the revenue that will be generated by diagnosing more patients will be far greater than the revenue that will be obtained by diagnosing a single patient. It is also our objective to increase robustness, efficiency, and accuracy in the health industry in order to save lives.

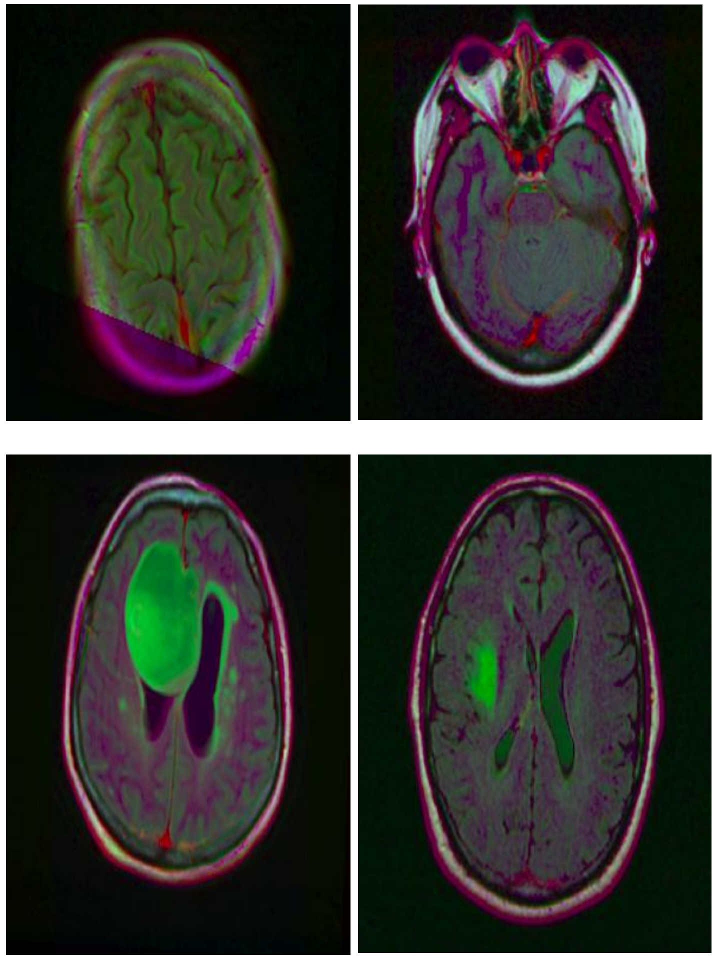
Success Metrics

Success Metrics What business metrics will you	Increased revenue generated via diagnosing a high number of patients in the health sector is the business metric that we would use to evaluate the product's performance in the market. If income increases and/or the number of deaths due to brain

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.	tumors decrease, the product is likely to be a success. We may gather data on income produced and the number of deaths before the product is implemented and compare it to data after the product is launched. This will help us to create a baseline value and give us a point of comparison.

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?	For this purpose, a variety of well-known research datasets are freely accessible in various data platforms such as Kaggle, and we could start using these data in our prototype. Because utilizing just academic data may not adequately reflect real-world situations. Therefore, we will gather certain data ourselves and annotate it using systems such as FigureEight. Because all of this data contains images of brain MRI scans, it is delicate, and we must be cautious and follow all applicable regulations. Which is why most academic datasets should not be used for business gain unless the dataset owner gives consent. Because data collecting and annotating is not a cheap job, it may cost anywhere from hundreds of dollars to tens of thousands of dollars, depending on the quantity of data we want to gather. We may gather data on an ongoing basis and update the model depending on how well it performs. As a result, we may have a total of 3000 brain MR images utilized for training by using 1500 images from an academic dataset, lowering the cost to approximately 3000–4000 dollars for acquiring and annotating the remaining 1500 images.
Data Source Consider the size and source of your data; what biases are built into the data and how might the data be improved?	The data comes from a combination of academic or research datasets as well as personal collections and annotations. When using academic datasets or when gathering data on your own, all of the images are typically taken with proper radiographic machines with clear imaging outputs. Thus, there may be a bias toward images taken by radiographic machines over images produced by a bad radiographic machine. If this is the situation, the model may not perform well on the images produced by the bad machine. Therefore, we must ensure that our data is balanced so that our model can perform well on any type of radiography. Furthermore, the photos we gather may be captured in different postures and perspectives beyond what our product would record in real time. As a result, you

	must ensure that your dataset takes this into account.  Fig1: Brain Tumor MR Images
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?	In this case, we have only one task to complete. That is, to detect the presence of tumors in the human brain using ML/AI and radiographic technologies, three labels were selected for this task which are “Yes”, “No” and “Unknown”. If there is a presence of tumor in the brain and if there isn't a presence of tumor in the brain, the answer is "yes," "no," and "unknown" to accommodate for ambiguity. This method simplifies and clarifies things more than other techniques because is a very straightforward data labeling method. However, in MR medical imaging, tumors in the brain are represented by a mask in the image.

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?	We will start with a simple prototype, utilizing automated ML services such as Google Auto ML or Amazon SageMaker to construct the model. Once we have confirmed that we are capable of completing the task at hand, we will examine the metrics to see if the model is producing results that are acceptable or in line with our objectives. If so, we will proceed with the model; otherwise, we will look for ways to improve the model, such as by adding more data. If we are still unhappy with the model's effectiveness, we will attempt to construct the model using the python programming language in recommended Integrated Development Environments (IDEs), since automated ML tools don't work in favor of our interests.
Evaluating Results Which model performance metrics are appropriate to measure the success of your model? What level of performance is required?	Precision, recall, and F1-score are all typical metrics that may be utilized to evaluate the performance of our model. Normally, we would want to correctly detect the presence of a tumor on all the images that are affected by a tumor. As a result, we want our model's performance metrics to be as high as possible, such as above 98.5% or 99.5%.

Minimum Viable Product (MVP)

Design

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

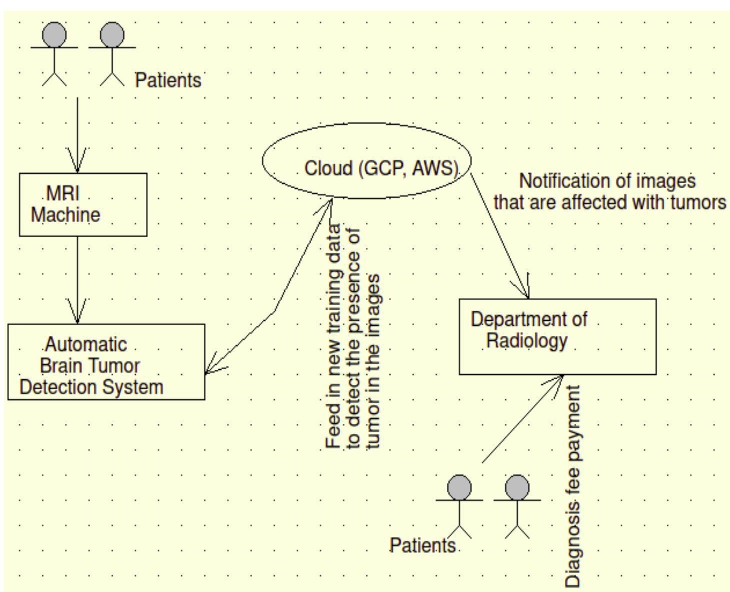


Fig2: Sketch of our product

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?	As previously stated, the health industry can use this product by feeding it with MR images of the brain to determine whether or not the image contains a tumor in the form of a mask. There are special charges attached to each patient which he/she must pay after going through this process. This product addresses the growing concern about inaccuracies in diagnosing brain tumors in the radiology department by providing almost 100% accuracy in perfectly diagnosing patients with brain tumors. The device also addresses the time-consuming diagnosis process in the health sector by diagnosing thousands of patients within a few minutes, which is really incredible in today’s medical situation.
Roll-out How will this be adopted? What does the go-to-market plan look like?	**Pre-launch:** Perform market research and analysis, thoroughly test our product, be ready to fulfill orders, and create public awareness about the use of the product, especially in the health industry. **Post-launch:** Track our product's performance and make improvements as needed; speak to consumers and get feedback; roll out new features; and, if necessary, address problems with the product.

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?	In the long run, the input data may vary from the data that the model was trained with. For example, individuals may have tumors in different locations in the brain, or the appearance of the tumor in the brain may change, for example, tumors might be scattered in the brain at different locations. Therefore, in order to account for all of this, we will need to continue gathering data and developing our model so that it can cope with any kind of input. We may train our new model with fresh data and use A/B testing to observe how the new model performs. We substituted the old model with the new one after confirming that our new model performed better than the old one via various metrics and iterations.

Monitor Bias How do you plan to monitor or mitigate unwanted bias in your model?	Let's say our model is good at identifying or detecting tumors in a single location in the brain and not at multiple locations in the brain or vice versa. Then, in any of these scenarios where the model is not doing well, we may provide additional data for the model and retrain it. We must constantly monitor where our model fails for whatever reason, like when the input data changes, and keep humans informed so that we may continue to improve the performance of our model in the interest of our business. However, we could focus on the following these 6 specific types of bias mitigations: 1. Identification of unwanted sources of bias 2. Identifying accurate representation of data. 3. Setting up proper rules and guidelines for eliminating bias & procedures 4. Documentation of how data is collected/analyzed and shared 5. Model evaluation for performance 6. A thorough and proper review of models that are being utilized in this project phase.

Appendix:

1. 6 Ways to reduce bias in machine learning and data analysis
https://searchenterpriseai.techtarget.com/feature/6-ways-to-reduce-different-types-of-bias-in-machinelearning#:~:text=Six%20ways%20to%20reduce%20bias,train%20the%20machine%20learning%20 model.

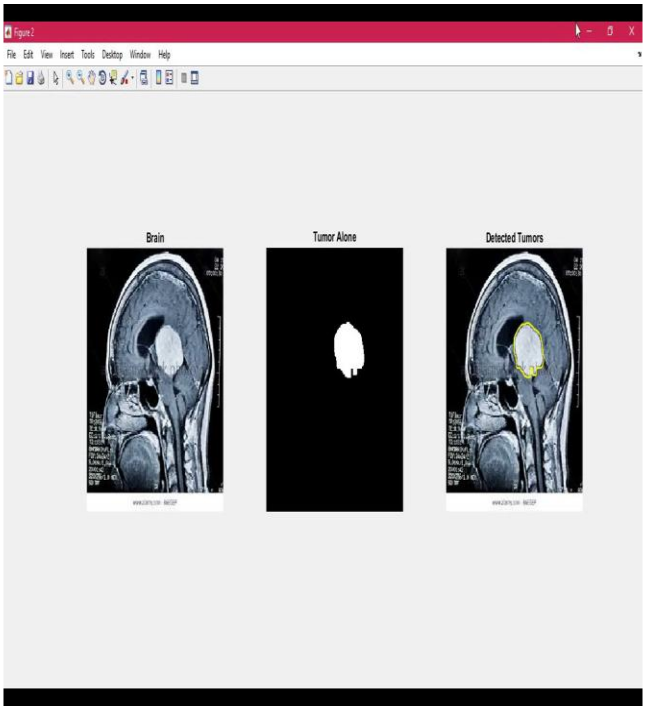
2. How to detect bias in AI
https://towardsdatascience.com/how-to-detect-bias-in-ai-872d04ce4efd

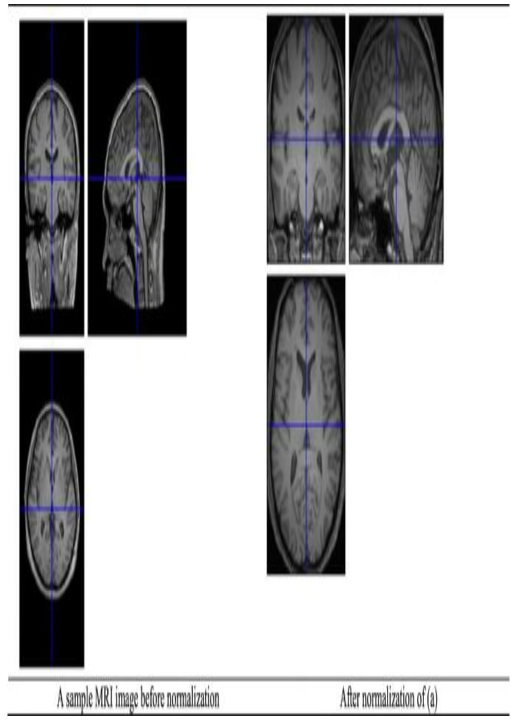
3. 3 performance metrics every business should know
https://www.inc.com/craig-bloem/5-key-metrics-every-early-stage-business-must-track.html

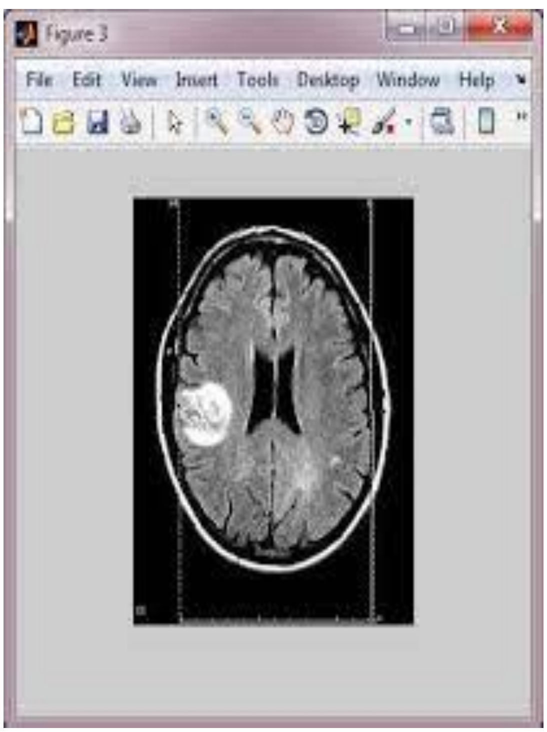
4. A/B Testing : What role does it play in the era of Machine Learning and A.I.
https://medium.com/capital-one-tech/the-role-of-a-b-testing-in-the-machine-learning-future-3d2ba035daeb

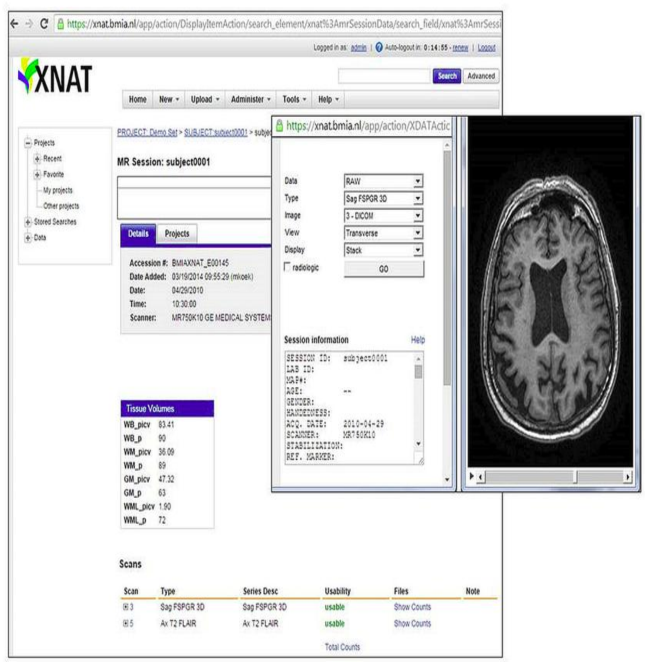
5. Proven Process for developing a ‘market-go-to-strategy’
https://blog.hubspot.com/sales/gtm-strategy

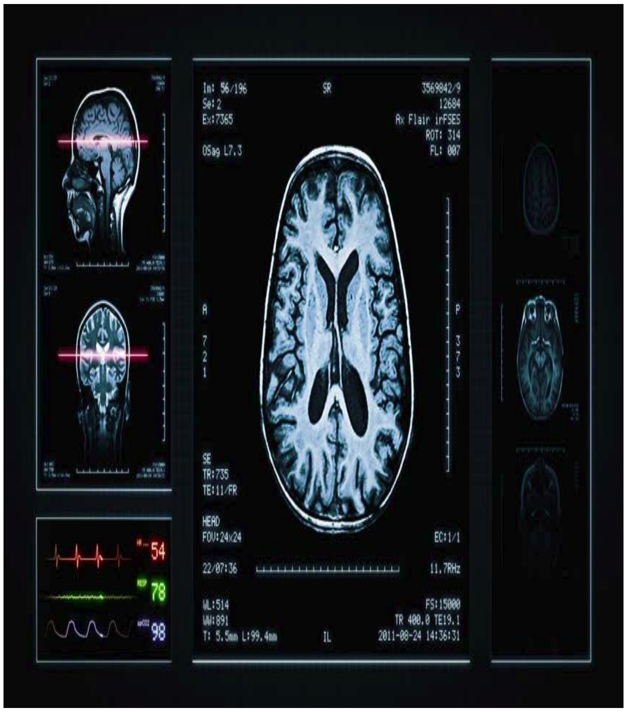
PRODUCT INTERFACE







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