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# **Proposal Report - Group 7.2**

Federated Learning

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Gastric cancer (GC) ranks fifth for incidence and fourth for mortality with over 1 million new cases and 768,000 deaths worldwide in 2020. These figures are a significant burden on health systems all over the world. Gastric cancer also carries a poor prognosis generally due to all to common late diagnosis of the disease and subsequent surgical intervention. The post operative care and scanning for reoccurrence is an opportunity to employ a federated machine learning product. Computer Vision models developed centrally then trained on local Data before being updated by a central server has the potential to both preserve Data privacy in addition to providing better quality models at the clinical front-lines thereby assisting physicians and reducing the burden on the already under stress health systems.

All members of Group 7.2 contributed equally to the paper bringing different strengths to the team. The team leverage tools such as GITHUB for code base sharing/ updating. Google Colab was used by some members. This report was written in 'Markdown' for pandoc. The group members are:

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*Cancer remains one of the leading causes of death worldwide, with approximately 20 million new cases and 9.7 million deaths reported in 2022.<sup>a</sup> Gastric cancer (GC) ranks fifth for incidence and fourth for mortality with over 1 million new cases and 768,000 deaths worldwide in 2020. These numbers are predicted to increase by 2040 with 1.77 million new cases and 1.27 million deaths worldwide predicted.<sup>b</sup>*

<sup>a</sup>“Global Cancer Burden Growing, Amidst Mounting Need for Services” (n.d.)

<sup>b</sup>Conti et al. (2023)

## Introduction

These figures are a significant burden on health systems all over the world. Gastric adenocarcinoma (GA) carries a poor prognosis generally as a product of the generally late diagnosis,<sup>1</sup>. This usually leads to a form of surgical intervention. Post operative care and support in the form of follow up scans and assessment of the scans is a significant burden on physicians already under pressure. There is a significant opportunity for Machine Learning to provide a level of assistance in the assessment of the follow-up scans.

The post operative care and scanning for reoccurrence is an opportunity to employ a federated machine learning product. Computer Vision models developed centrally, then trained on local data before being updated by a central server has the potential to both preserve data privacy in addition to providing better quality models at the clinical front-lines thereby assisting physicians and reducing the burden on the already under stress health systems.

It is anticipated that a Machine Learning product developed and deployed in a federated learning construct, when combined with other markers has the potential to assist physicians in making faster, more accurate diagnosis allowing them to take action early in an effort to beat the disease.

## Gastric Cancer

Gastric cancer (Gastric adenocarcinoma) is the most common type of gastric cancer. According to the Cancer Australia<sup>2</sup> there are three other types of cancer that are more rare but can be equally devastating, these are: - Gastrointestinal stromal tumours - start in the connective tissue in the stomach wall - Lymphomas - start in the lymph system - Carcinoid tumours - start in the hormone-making cells

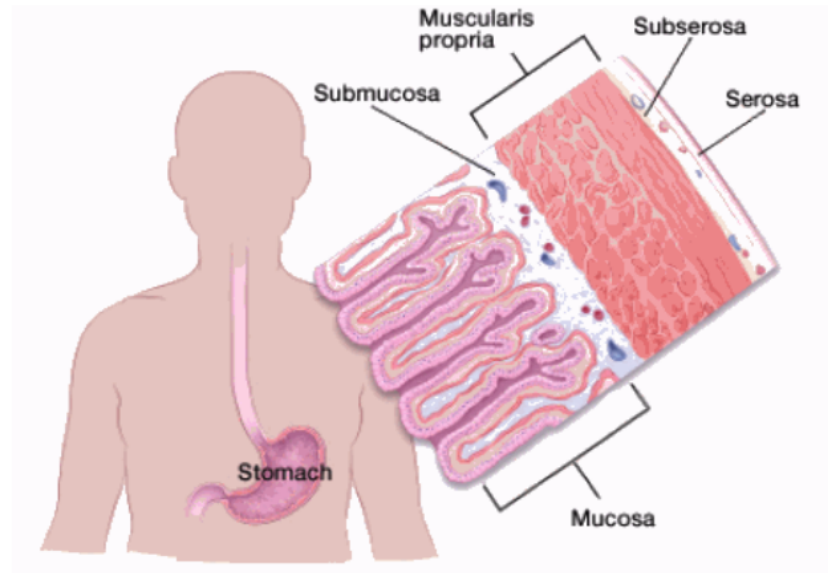
Gastric Adenocarcinoma (GA) starts in the glandular cells in the inner layer of the stomach wall (mucosa). It then moves into the submucosa before moving deeper into the muscularis layer surrounding the

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<sup>1</sup>Banks et al. (2019)

<sup>2</sup>“Types of Stomach Cancer \Textbar Cancer Australia” (n.d.)

stomach. Another key concern with stomach cancer the proximity to the lymph nodes and the potential for the cancer to subsequently spread throughout the body.<sup>3</sup>



**Figure 1:** Stomach Wall Details

If the disease can be diagnosed early then the treatment and subsequent outcomes can be very positive. It usually starts as a polyp on the stomach wall, many people that have these polyps are asymptomatic. Only at the onset of symptoms generally does a physician get consulted and an investigation subsequently commence. The traditional treatment for gastric cancer typically involves a combination of surgery, chemotherapy, and radiation therapy. Surgery, such as gastrectomy, is by far the primary treatment. Chemotherapy and radiation therapy may be used before surgery to shrink the tumor or after surgery to eliminate remaining cancer cells. A substantial portion of gastric cancer patients necessitate surgical intervention. Notably, a study revealed that approximately 50.5% of patients with gastric adenocarcinoma underwent lymphadenectomy, underscoring the high prevalence of surgical procedures in the treatment of gastric cancer (F.B. et al., 2023). The recurrence rate of gastric cancer following surgery is significantly high. Research indicates that over 60% of patients experience a recurrence of the disease within two years post-curative resection (WJSO, 2016).

Principle in identifying and treatment and post operative care following surgery is some kind of imaging system. The images taken are generally taken with some form of endoscopy (either white light or magnifying), magnifying endoscopy (ME) has been found to be more accurate.<sup>4</sup> In 2016 the first 8k endoscopes were used in a clinical setting.<sup>5</sup> This high quality imagery taken as part of the ongoing

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<sup>3</sup>“Stomach (Gastric) Cancer Stages \Textbar How Far Has Stomach Cancer Spread?” (n.d.)

<sup>4</sup>Le et al. (2021)

<sup>5</sup>Yamashita et al. (2016)

diagnosis and treatment of GA presents as a significant opportunity for computer vision models - particularly when applied in a federated learning setting. The study on which this premise is based used CT images that were taken from post operative patients.

**Risk** It is uncertain what kind of imagery is taken as part of patient post operative follow up. The available data is a series of CT scans. There is limited to no known endoscopic images for the purposes of training a CV model. It is uncertain if CT images are used for post operative follow up in the Australian context.

## Computer Vision

Computer vision as a field of study has a rich, elongated history spanning many decades. The application of the benefits from field in the medical domain were immediately obvious to many. Techniques such as image segmentation have seen significant advancements with the development of neural networks. Prior to the development of advanced optimisation techniques assessments of volume assessments of tumors generally required laborious hand tracing of anticipated outlines on scans and x-rays. Image segmentation and edge detection techniques were then applied to classification tasks thereby reducing diagnosis times by assisting physicians and speeding the process for the entire system. These systems require data to train on, in the medical setting this data is heavily governed and sensitive in nature. Accessing and using it to develop models can be complicated. Techniques such as Federated Learning have something to offer in this context.

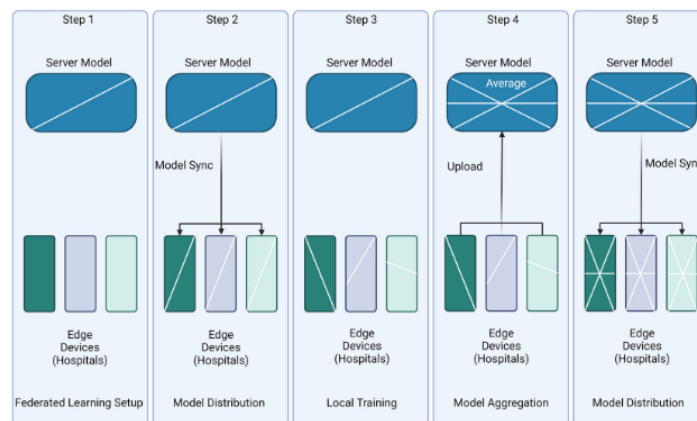
## Federated Learning

Federated learning was introduced in 2016. Since its introduction this ML technique has been used across a number of different domains.<sup>6</sup> Of note, the proposition of preserving the integrity and privacy architectures associated with Data is of significant interest to the medical field and central to this proposal. The ability to apply best of class computer vision models across a number of clinical data sets while preserving the privacy and security considerations has the potential to propel the use of ML in the medical field significantly. Furthermore, federated learning has the ability to aggregate the strengths of the individual models in each clinic and develop a better model in the clinical setting. An example of the federated system is below:<sup>7</sup>

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<sup>6</sup>Sandhu et al. (2023)

<sup>7</sup>Sandhu et al. (2023)



**Figure 2:** Federated Learning System

This production and deployment method for models is one that carries significant benefits for any industry that is concerned with Data privacy or small *silos* of datasets.

## Outcomes

The task for the group as defined in the statement of requirements is to:

*The ultimate goal is to create a powerful predictive tool that can be deployed across various health-care settings, enabling early intervention and personalized treatment plans for patients at high risk of gastric cancer recurrence, while maintaining data privacy and security*

This goal will involve several phases, the list below highlights key tasks but is in no way exhaustive:

- Establish the context to the local medical field.
  - Is there a requirement for this sort of product in the context specific to gastric cancer?
- Gather suitable and relevant data.
  - Data Process inclusive of cleaning and verifying
- Develop a single computer vision model capable of classifying images of gastric cancer
  - Understand the accuracy metrics and context for a computer vision model in the medical context.
  - Provide a framework for how the model can be used.
- Develop the framework to deploy the model in a federated learning setting.



- Detail the hardware and software requirements in the various clinical settings.
- Provide a list of ethical considerations for the use of the single model and the federated model in the clinical setting.

While these are only a few points each of these will carry a significant number of sub-steps that will need to be bounded in both available resources and the anticipated deployment context.

## **Value Proposition**

The value proposition is comprised of three separate dimensions. There is a dimension specific to gastric cancer and how Machine Learning can assist in post operative care. There is a dimension of a single Machine Learning model in a single clinic context and the value it can add. Finally, there is the value that a federated system can bring. The federated learning system is anticipated to produce a more generalisable model, potentially overcoming bias associated with demographics in narrow populations in addition to reinforcing Data privacy and security in a highly sensitive context.

While these are the expected benefits there is also some of the ongoing costs associated with developing the *product* in addition to the ongoing maintenance and upkeep on a system that supports these kinds of products. As yet the costs associated with this are not known but will form a key element of the ability of this kind of system to go into production in a mature state with ongoing support and sustainment.

## **Literature Review**

### **The Medical Issue**

The usage of different follow-up techniques for post-operative care and what imaging systems present the most opportunity?

### **Types of Scans**

The treatment of GC has become increasingly multi-modal, critical in the treatment both pre-operative and post-operative is the use of imaging technologies, particularly computed tomography(CT).<sup>8</sup> PET/CT scans are particularly useful for detecting recurrence, although their sensitivity can vary depending on the location of the recurrence (Ma et al., 2023). Other factors relating to PET/CT scans have also reduced the effectiveness of the techniques such as time to complete the scan (2-3 mins), the uptake of the dye marker(F-Fluoro-Deoxy-Glucose (FDG)). Specific to FDG, the uptake of the marker has shown a

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<sup>8</sup>Hu et al. (2012)

large variance in different patients resulting in variability in the quality of the images when compared with the CT by itself.<sup>9</sup> (Jayaprakasam, Paroder, and Schöder 2021) Ultimately this leads to a significant variability in the quality of the images used to assess and identify the recurrence of GC. These scans can produce false positives or negatives, leading to unnecessary procedures or missed diagnoses. Additionally, traditional tumor markers lack specificity and sensitivity, making them less reliable for early detection and monitoring (Ma et al., 2023). Endoscopy, while effective, is invasive and can be uncomfortable for patients, with a sensitivity of only about 69% for screening<sup>9</sup>.

In addition to the types of scan an emerging area of medical image analysis is radiomics. Radiomics is an emerging area in quantitative image analysis that aims to relate large-scale extracted imaging information to clinical and biological endpoints.<sup>10</sup> This takes the field CV one step further and combines the extracted image features with bio-markers taken from other elements of patient data in an attempt to personalise both the identification and the treatment plan into the future. Radiomics is also claimed to be capable of predicting survivability of patients with GC.<sup>11</sup> In saying that, the application of this field in a clinical setting isn't yet at a point where it can be trusted due to immature phases, relatively poor quality, and significant methodological heterogeneity in the radiomic workflow.<sup>12</sup>

The use of CT scans in the current context appears to be the most stable and reliable imagery to be used for the development of a federated learning system leveraging deep learning techniques. While there may be inconsistencies in the image quality across all images available and accounting for variability between systems it presents as the greatest opportunity as it is widely accepted and applied in post-operative followup context.

### **Ethical Considerations - Links are wrong in text doc**

Federated learning in healthcare, particularly gastric cancer, raises several ethical concerns. One major issue is data privacy. While federated learning aims to protect patient data by keeping it decentralized, there are risks of data breaches and re-identification of patients<sup>13</sup>. Additionally, bias propagation is a significant concern. Federated learning models can inadvertently amplify existing biases in the data, leading to unequal treatment outcomes for different patient groups (Doe, 2022)[<https://arxiv.org/abs/2309.02160>]**Check Ref**. Furthermore, the fairness of the models is questioned, as the quality of data from different institutions can vary, potentially disadvantaging patients from less resourced hospitals<sup>14</sup>.

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<sup>9</sup>Hu et al. (2012)

<sup>10</sup>Avanzo et al. (2020)

<sup>11</sup>Chen et al. (2022)

<sup>12</sup>Chen et al. (2022)

<sup>13</sup>Yuan, Wang, and Brinton (2023)

<sup>14</sup>Bak et al. (2024)

## The Model Options (Background)

In Machine Learning, particularly where explainability is a critical element there is an onus to keep things as simple as possible to enable explainability for both the clinician and the patient population.<sup>15</sup> The ability to say why things are the way they are is an essential element when it comes to both technology adoption and patient comfort. An example of a comparatively simple model deployed in 2009 focussed on cervical and head and neck cancers.<sup>16</sup> This work demonstrated promising results in developing a combination model intensity volume metrics combined with shape and texture feature extractions. One weakness of the study was the small population base ( $n=14/9$ ). A key difference was the type of image gathered in this study, FDG-PET scan imagery was used rather than MRI imagery making the procedure more invasive. A key consideration for follow-up patient care following potentially aggressive treatment.

Other techniques that haven't used a Neural Network include Bag of Visual Words (BoVW), Support Vector Machine(SVM), histogram of gradients(HOG), local binary pattern (LBP). Used in isolation there have been some promising results in high-contrast contexts. These techniques are now starting to be combined with Neural Networks in different techniques and methods. Some of the methods are delivering promising results in specific settings.<sup>17</sup> The combination of both *classic* techniques and *neural networks* is an area of research gaining new interest. This may be in part as the growth of Neural Network innovation begins to slow in relative terms when compared to the last few years.

In the context of federated learning for detecting gastric cancer recurrence, the client model utilizing CNN models like VGG and RESNET play a crucial role. ResNet19, a variant of the Residual Network (ResNet) family, is designed to mitigate the vanishing gradient problem through the use of residual connections, allowing for the training of deeper networks without performance degradation (He et al., 2016)(He et al. 2016). This architecture is particularly effective in medical image analysis, where capturing complex patterns is essential for accurate cancer detection (Smith et al., 2023)[<https://arxiv.org/abs/2310.03178>] **Check Ref** Implemented in PyTorch, ResNet19 can be fine-tuned on local datasets from different institutions, enabling the model to learn from diverse data while preserving patient privacy (Doe, 2022)[<https://arxiv.org/abs/2309.02160>] **Check Ref**. The federated learning approach ensures that the model benefits from a wide range of data without compromising the confidentiality of individual patient records, thus enhancing the robustness and generalizability of the cancer recurrence detection system.

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<sup>15</sup>Shukla et al. (2020)

<sup>16</sup>El Naqa et al. (2009)

<sup>17</sup>Marzouk and Elkholy (2024)

### **Building a Model**

Building both client and federated models from scratch can be time-consuming and resource-intensive. This approach involves creating the entire architecture of neural network and training without relying on any existing models. Some limiting factors associated with this approach include the time available, the amount of compute available to the group, the high end expertise at the individual level. These factors are limitations that the group cannot overcome in the short term and the results of the proposed model would not be good enough when compared to the results of an already developed advanced framework.

### **Transfer Learning**

Transfer learning seeks to take pretrained models and apply them in a specific context. This has the potential to overcome some of the weaknesses identified above.<sup>18</sup>

Using pretrained models for clients then fine-tuned to the local datasets before aggregating the retrieved weights to the central server for federated learning will significantly reduce the computational resources. A study by Tan et al. (2022) proposed a lightweight federated learning framework that uses multiple fixed pretrained models. The study found that using pretrained models does not significantly affect the federated learning process and can improve the efficiency and performance of the system.<sup>19</sup> Additionally, in real-world scenarios, it is not practical to build models from scratch due to data availability, computational resources, and etc. Using pretrained models will standardize the primary state of federated learning.

### **The Federated Learning**

Federated learning is an emerging approach in healthcare, which is valuable for sensitive data like medical images. It allows multiple institutions to collaboratively train a model without sharing patients' data, thus preserving privacy. This review focuses on the application of federated learning for detecting the recurrence of gastric cancer in which client models are developed through ResNet19 and VGG16 implemented by PyTorch.

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<sup>18</sup>Kim et al. (2022)

<sup>19</sup>Tan et al. (2022)

## **Outcomes**

## **Timeline**

## **Project Schedule**

## **Resource Allocation**

## **Considerations**

## **Skills in the Group**

## **Resources Allocation**

## Assignment Task for Reference - to be removed

This project aims to develop a federated learning model to identify high-risk patients for postoperative gastric cancer recurrence. Gastric cancer remains one of the leading causes of cancer-related deaths worldwide, and early detection of recurrence is crucial for improving patient outcomes. However, the sensitive nature of medical data often limits data sharing and comprehensive model training. Federated learning offers a solution by enabling the training of a robust predictive model across multiple healthcare institutions without sharing patient data. Each institution trains the model locally on their data, and only the model updates are shared and aggregated, preserving patient privacy. The project involves the following key steps: 1. Model Development: Designing a federated learning framework tailored to predict postoperative recurrence of gastric cancer, leveraging advanced deep learning techniques. 1. Training and Validation: Implementing the federated learning model, ensuring effective communication and aggregation of model updates from different institutions, and validating the model's performance.

The ultimate goal is to create a powerful predictive tool that can be deployed across various healthcare settings, enabling early intervention and personalized treatment plans for patients at high risk of gastric cancer recurrence, while maintaining data privacy and security.

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