Final Report

AUSTRALIAN MEAT PROCESSOR CORPORATION

Teys Smart Vision

A1 Computer Vision - Activity Based Monitoring Across Specification, Cut and Yield

Project Code
2022-1124

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Date Submitted
31/01/23

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1.0 Executive Summary

This project was to deliver an activity-based costing solution for a subset of the Teys Beenleigh Processing Plant. The solution was novel, as smart vision technology was proposed (fixed video cameras and machine learning) to track product harvested from carcases and measure time in motion for each product prepared at in scope boning and slicing tables.

Machine Learning algorithms were iteratively developed over many months to classify the process steps and measure time spent on each process step. At the outset it was unclear the level of accuracy that could be achieved and the associated development timeframes to meet Teys' requirements. Delivery timeframes were underestimated and the overall project duration was extended. The team faced, and overcame, many challenges in developing accurate classification models for the different time in motion process steps. The iterative development process involved training and retraining the algorithms with additional data and incorporate feedback from the Teys project team to improve their accuracy. Additionally, the team was required to adjust the models as they encountered new data (either camera position adjustments/new products) and make ongoing improvements to the algorithms.

In milestone 4, the solution was proven to accurately record time in motion measurements partially achieving the projects overall objective, however technical limitations were encountered and not overcome during the project. These related to the linking of time in motion measurements with the corresponding carcase record. Without this information, the time in motion data could not be accurately linked back to the carcase or product code. This limitation restricted the overall impact the project had. Teys will continue to explore options to address this linkage of carcase post project.

2.0 Introduction

The challenge of accurately measuring processing time and linking it accurately back to an individual carcase is a significant one. The complexity of processing beef at scale means that traditional costing methods are often inadequate for accurately measuring the cost of labour required to prepare each product. With somewhere between a quarter and a third of all slaughter cattle in Australia being processed for service kill customers, the ability to accurately attribute costs through the boning room was identified as a major step forward for industry. This is particularly true for low margin high volume beef processors. As a result, the need for a solution that would enable the measurement of processing time and link it back to each carcase at scale was identified.

To achieve this goal, the project team proposed the use of smart vision technology to track the products harvested from carcases and measure the time spent on each process step. The solution involved using fixed video cameras and machine learning algorithms to accurately classify the process steps and measure time spent on each step. By achieving this, it would enable Teys to accurately measure the cost of labour required for each product and make data-driven decisions to optimize their operations.

The project aimed to capture time in motion data that related to the corresponding carcase without changing the Beenleigh boning room footprint/configuration or impacting productivity. This approach meant that Teys could measure processing time each and every day without introducing additional productivity constraints or expensive investments, instead of assessing likely processing time based on a few examples. Teys was aware that engineered solutions exist in the market, however in addition to the expensive nature of the required investments, productivity constraints would be introduced. This project aimed to capture time in motion data that relates to the corresponding carcase without changing the Beenleigh boning room footprint/configuration or impacting productivity.

3.0 Project Objectives

3.1 High Level Objectives

The high-level objectives of this project were to develop software solutions and innovations to the industry including the following:

Red meat yields delivered in real time – Developing a complete 1 to 1 traceability system would enable individual cut pieces to be weighted a point along the production line and linked back to a carcase side. This would provide accurate red meat yields in real time to management within the boning room. Further, using the grading information from a particular carcase, including fat depth, weight and marble score, algorithms could establish an expected yield for each individual cut. This information would provide detailed benchmarking to management for decision making in real time.

Training - Using individual cut yields delivered in real time along with measurements of processing time, an objective of the project was for management to get better and faster access to information, that would identify employees who required additional training and resources. Currently with reporting often done at a batch level and either hours later or the following day, it is difficult for management to provide support or corrective action in a timely manner. An objective was to use the real time data generated to reduce the information gap and assist with employees training, thus improving the quality of the product.

Gamification – Using individual cut yields delivered in real time along with measurements of processing time, a future object was to use better information for measuring and comparing performance amongst workers. By making live yield and timing data available via screens or reports to skilled workers on the floor, the objective was to drive improved performance. Currently little information is shared with workers and the comparison on performance is by management. Using actual data and the natural competitive nature of people, sharing this information would almost certainly improve performance. Further, within the industry most skilled workers are paid a standard rate that is not reflective of individual performance. There may be scope in the future where detailed data provided by a system like this, may be use for individualised remuneration.

3.2 Detailed Objectives

The detailed objectives of this project were to develop a smart vision solution that enabled accurate analysis of the following areas:

1. Correctly tracking each unique cut harvested through to a bagging station and associating it back to a single carcase.
2. Correctly tracking each unique cut from the bagging station through to the box and associating it back to a single carcase.
3. Measuring and correctly associating processing time for each area to a cut specification.
4. Utilising Lumachain's Track and Trace System to provide data feeds as required for the Teys Data Warehouse in near time throughout operations.

By achieving these objectives, Teys would be able to accurately measure the cost of labour required to prepare each product, enabling data-driven decisions to optimize operations and remain commercially competitive. In summary, the objectives of this project are to develop and implement a smart vision solution that will enable Teys to accurately measure processing time and track and trace in-scope product from Boning station to Slicing station to Bagging station at Teys Beenleigh. This solution will provide Teys with the data they need to make informed decisions and optimize their operations, improving their ability to compete in a complex and challenging industry.

4.0 Methodology

- Installation of equipment and hardware required for data collection.
- Data collection, integration, and development (a combination of multiple on-site and off-site activities)
- Sign off by Teys and AMPC against project outputs/deliverables.

4.1 AI Development

Throughout the project, AI development was a continuously improved and remodelled to meet the project objectives. The process undertaken is explained below.

4.1.1. Initial Time in Motion Development

The initial focus was to develop models for measuring processing time across each of the following areas for boning and slicing; total contact time, knife sharpening time, slicing/boning time, idle time of the employee. At this stage there was no link between carcase and primal, nor where individual tables or regions of interest identified. An example from the user acceptance testing conducted is shown below.

At the time of this snapshot the below was observed in relation to the average boning times per side:

Knife Sharpening: 7 seconds

Boning (removing): 48 seconds

Idle time between carcases: 17 seconds

At the time of this snapshot the below was observed in relation to the average slicing times per primal:

Knife Sharpening: 8 seconds

Trimming (per cut): 19 seconds

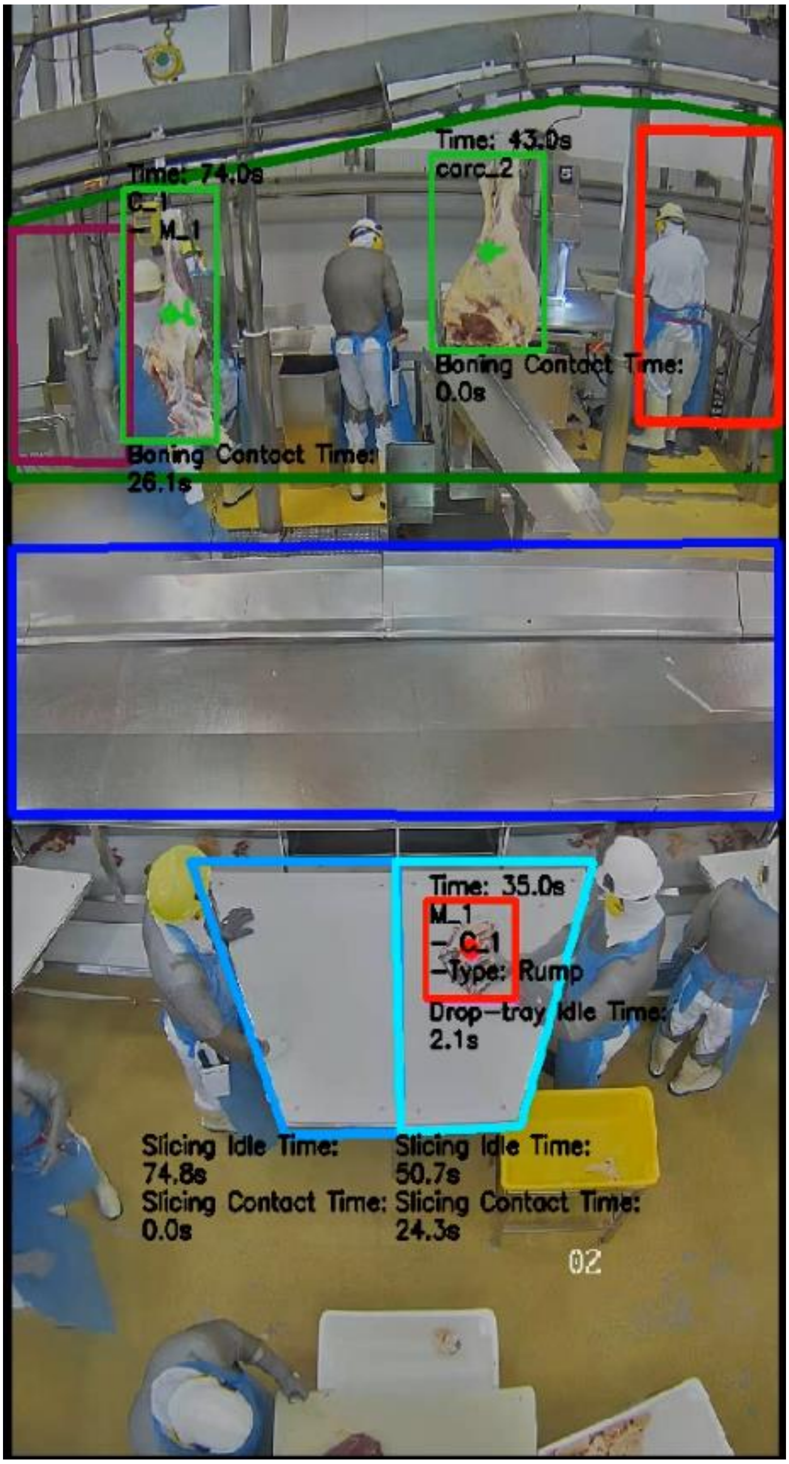
Slicing (per cut): 15 seconds

Avg time primal on the table: 53 seconds

Idle time between cuts: 10 seconds

4.1.2. Traceability Development

The next stages of development included defining regions of interest and beginning to develop a link between carcase and primal. The development also included the early work on cut recognition. Measures for time in motion were refined and continued to be included in the algorithms. An example from the user acceptance testing conducted is shown below.



This shows carcases sequentially identified by integers for the first time.

Boning region of interest is shown in dark green.

Drop Tray region of interest is shown in dark blue.

Boning Contact Time is measured.

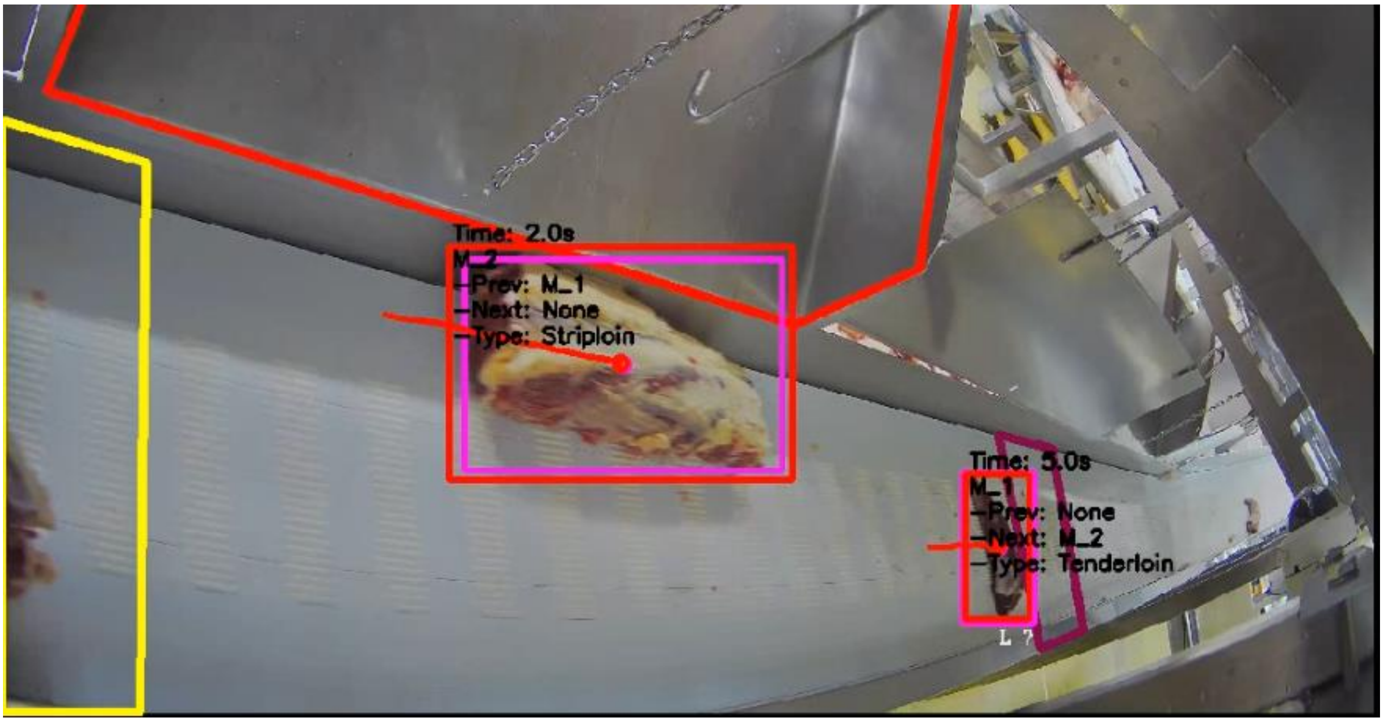
This shows primals sequentially identified by integers for the first time. It also shows the link between meat (M) and parent carcase (C). The cut recognition is showing correctly as rump

Slicing region of interest is shown in light blue.

Slicing Idle and Contact Time is measured.

4.1.3. Traceability Development (Primal Belt)

Different models were developed for cut recognition and movement of primals along various conveyors. An example from the user acceptance testing conducted is shown below. In this the cut recognition model has incorrectly identified a cube roll as a striploin. As the models were developed from stations 7 – 10, cuts from the forequarter were not considered in the development.



4.1.4. Real Time Data Delivery

Dashboards to deliver data in real time were developed. An example is shown below.

Activity Costing Report for Rump at Station 8

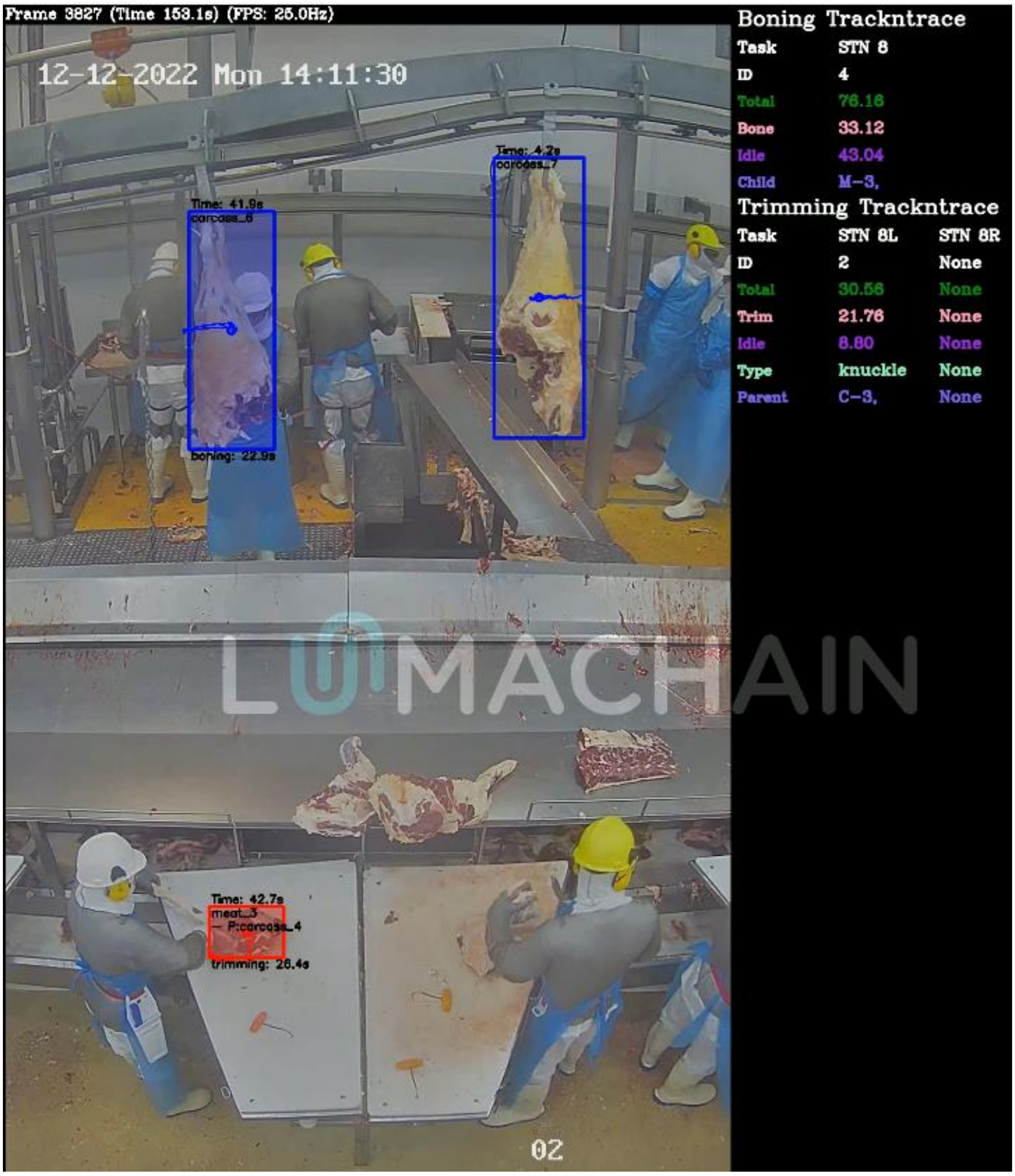
Processed Meat #	Average Boning Time	Average Slicing Time
4	14s	31s

Carcass ID	Employee ID	Table	Type	Knife Sharpening	Remove Rump
#C001	#E001	Right	Rump	12	10
#C002	#E001	Right	Rump	0	9
#C003	#E001	Right	Rump	0	12
#C004	#E001	Right	Rump	0	11

Meat ID	Employee ID	Table	Type	Knife Sharpening	Trimming Rump	Trimming & Slicing Tri Tip	Trimming & Slicing Rostbiff/Cap
#M001	#E002	Right	Rump	0	8	6	15
#M002	#E002	Right	Rump	0	9	7	16
#M003	#E002	Right	Rump	10	10	8	14
#M004	#E002	Right	Rump	0	9	6	16

4.1.5. Further Traceability Development

Below shows a snapshot from the user acceptance testing conducted as part of Milestone 4. The focus was to increase the levels of accuracy on the link between parent carcase and primal whilst still providing accurate time in motions measures.



5.0 Project Outcomes

5.1 Objective 1 and Objective 2: Tracking of cuts harvested to a single Carcase

Objective 1 was deemed as foundational, and 23 CCTV cameras were installed with overlapping fields of view to follow carcases and cuts for in scope product at Teys Beenleigh. The high level product flow was as follows:

Boning Station -> Drop Tray -> Slicing Station -> Primal Conveyor -> Bagging Station

The majority of the cameras were positioned over primal conveyors and bagging stations. Significant technical challenges were identified during the project relating to the tracking of product at the (5.1.1) Drop Tray and (5.1.2) Stitching camera footage for traceability, i.e. tracking the piece across multiple camera feeds. The Drop Tray issue hampered the projects overall ability to link time in motion data with the corresponding carcase and associated specifications.

5.1.1. Drop Tray Challenges

Cuts touching on the drop tray were incorrectly classified as a single piece resulting in anomalies in the data, i.e. duplicate records for a single piece or data gaps. This happened often as the drop tray at Beenleigh was ergonomically designed to slide pieces ‘dropped’ onto the tray down towards the Slicing table to reduce unnecessary movement and strain on the Slicer. The term stacking was used throughout the project, however this didn’t necessarily mean product was stacked on top of each other and the piece was no longer visible. The project team identified that this scenario occurred frequently throughout the day when 3 or more cuts appeared on the drop tray. This challenge was not overcome and as a work around, the vendor switched to time based First in First Out (FIFO) tracking for the drop tray. When product flow differed, for example a cut enters the drop tray first (meaning, boning off the carcass first) but does not exit first (meaning, taken from the drop tray by the slicing/trimming worker for processing). This invalidated the entire FIFO assumption for time-based association. Testing revealed that this FIFO method was circa 20-25% accurate depending on the Teys production scenario and impacted the overall reliability of the results. This problem caused issues around AI ID skipping which resulted in false positive meat cut detections, causing the skipping of integer indices. During pre-processing, the module assigns unique integer IDs in an incremental manner to every detected meat cut, however, not all detected cuts are considered a genuine as they must pass the stringent post processing phase and qualify on all filtering standards to be considered as a genuine cut (e.g., one standard requires the meat cut time to exceed N seconds).

The issue relating to the touching of cuts was not limited to the Drop Tray. Different primals or cuts that were next to one another could merge into one piece (via the model’s interpretation), causing AI model ID shifting between the different primals and combining model ID’s for 2 pieces as seen below in Image 1.

Image 1. Knuckle Slicing Table Product Touching

Towards the end of Milestone 4, the vendor, Lumachain, advised that a ‘clean’ workflow should include the following:

1. Carcass to be boned in alignment with the table. i.e., carcass to be directly above the slicing table.
2. All production for a primal to happen within a single field of view for a camera
3. One table to trim one type of primal at a time.
4. No stacking of meat – maximum of 3 cuts on the drop tray, maximum of 1 cut per slicing table and for each cut to be clearly away from one and other.

The real time traceability of carcass to cut was demonstrated on 10 minutes of production footage with a ‘clean’ workflow. This was done at the knuckle station only which met the required criteria during the testing period. For this time window, the model was able track product from Carcase to Drop Tray to Slicing Table without issue.

Teys is not able to produce the ‘clean’ workflow proposed by Lumachain due to production complexity.

5.1.2 Challenges around stitching

Lumachain were unable to demonstrate the ability to stitch footage between cameras and follow product from Boning Station to Bagging Station. Lumachain was unable to stitch footage and AI ID’s across multiple fields of view, which would be required to provide complete data for its intended purpose. Given the challenges identified at the Drop Tray, real time stitching of camera feeds was de-prioritised. Teys is confident that alternative methods exist for tracking product from primal conveyor to bagging and then on to a carton/crate.

5.2 Objective 3: Measuring and correctly associating processing time for each area to a cut specification.

Objective 3 was achieved and results associated back to a cut specification. Good levels of accuracy were achieved for Boning and Slicing, however given the challenges highlighted earlier with Objective 1 & 2, the two measures could not be accurately linked consistently. As per the Milestone 3 Report, Time in motion algorithms developed by Lumachain continue to provide data back to Teys daily, through an online portal. Time in motion models continue to be refined but show good levels of accuracy, particularly for boning workflows.

5.3 Objective 4: Data Feeds into Teys Data Warehouse

The project established a mechanism to receive track and trace data feeds on a daily basis into the Teys data warehouse.

6.0 Conclusions / Recommendations

This project aimed to provide traceability of product and record time in motion data for boning and slicing process steps at in scope stations at Teys Beenleigh. The objective of the project was to gather time in motion data that is linked to the corresponding carcase, while keeping the Beenleigh boning room footprint and configuration intact and without affecting productivity. Allowing Teys to measure processing time on a daily basis without adding any productivity limitations. The project partly met these objectives using Smart Vision technology. With the current boning/slicing processes and boning room footprint achieving high level of accuracy with the AI algorithms has proven extremely difficult. Time in motion recording has been demonstrated as successful, however significant progress needs to be made before the AI algorithms can be relied on for traceability during normal production. The team is continuing to explore building in further smarts to identify when tracking can be relied upon or not for a given carcase. For example, if the traceability solution is accurate 20-25% of the time, can we tell which 20-25% of product was likely to be accurate with tracking.

Another set of ongoing challenges relate to the stitching between cameras. Development was largely put on hold to address this capability, and Teys believes that other technologies should be explored when tracking from primal belts to bagging and then eventually to a carton. In terms of recommendations, it is suggested to keep project scope very small and achievable, verify vendor capability of core components such as stitching between cameras in real time and traceability outside lab tests before commencing.