Final Report

AUSTRALIAN MEAT PROCESSOR CORPORATION

Box Label Verification

Computer Vision verification technologies to reduce labelling errors in the red meat processing industry

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Prepared by
Stuart Smith, Josh Hall, Jon Marshall

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1.0 Executive Summary

The Australian red meat processing industry is a critical contributor to the country's economy, with meat exports being a significant part of the industry. The industry has been identified as a priority sector for investment, with the Australian government providing funds to modernise meat processing and make it more competitive. One key aspect of the modernisation process is the improvement of regulatory activities, including the development of electronic processes to replace paper-based forms and the implementation of "smart" technologies for verification activities.

Quality control is a vital aspect of the red meat processing industry, particularly regarding the packing and labelling of meat into boxes. The industry has previously faced issues in this area, with human error leading to labelling inconsistencies and subsequent export bans. These errors have significant consequences for individual processors and the entire Australian meat processing industry, resulting in significant financial loss, damaged reputation, and loss of market share.

To address these issues, the project builds upon earlier AMPC-funded research (2021-1113) which in-part, explored development of a prototype computer vision-based solution capable of detecting box label errors found in meat processing factories. While the previous project was able to demonstrate that computer vision systems employing artificial intelligence (AI) could detect several cuts of meat, and that a combination of traditional computer vision and AI could extract information on external box labels, it concluded that further development of a box label verification solution for use by Australian meat processors required further investigation.

Moving from a prototype box label verification solution to a robust commercial solution that could be deployed into a meat processing facility requires addressing several challenges. One of the challenges is ensuring that the solution is robust and reliable enough to work in a real-world meat processing environment, which involves various operating conditions such as a requirement to withstand harsh, end-of-shift cleaning regimes involving high pressure water jets within boning rooms.

Commercial vendors of industrial automation technology can bring several capabilities to the solution, such as expertise in designing and implementing automation systems, knowledge of industry best practices, and access to a wide range of technologies and components. They can also provide support for maintenance and troubleshooting, as well as ongoing training and education to ensure that the solution is used effectively. Consequently, this project aimed to work closely with several vendors of industrial computer vision solutions to explore if “off-the-shelf” technology could be deployed into meat processors to address the label verification challenge.

In addition to label verification the project aimed to explore whether advanced AI computer vision techniques could be used to analyse human “pick and place” tasks to help answer the critical question of “What cut of meat did a process worker pick and place into the box?” This project addressed the challenging problem of ensuring that process workers correctly identify, select and pack cuts of meat into a box. Combined with analysis of the information content and placement of box labels, the projected aimed to significantly improve label verification in the red meat processing industry.

The objectives of this project were therefore the following:

- Consult industry about their direct needs for label verification.
- Conduct staged comparative experiments of existing off the shelf solutions which could solve this issue.
- Field trial at least one label verification system which has passed prior evaluation steps.
- Conduct staged experiments of “What was put in the box” computer vision solution to detect meat cuts placed into a carton.

- Field trial prototype of “What was put in the box” computer vision solution in a meat processing facility that links with a label verification system.

This project pursued a sequential staged approach involving research, design, development and testing. Each of these stages had their own sub objectives and outcomes. To summarise, the stages were:

- Research: Further understand the challenges faced by the meat processing and inspection industry
- Design: Experimentation design, installation, rollout procedures for the labelling solutions. Data capture in the field used for training AI model.
- Develop: Develop additional experiment materials and software to support the use of these camera systems in a meat processing environment. Develop AI models to be used with these systems.
- Test the use of the technology being applied to challenges in food safety inspection, data capture.

Outcomes from the project included:

- while many meat cuts are relatively easy for humans to discriminate, several cuts, especially when shrink wrapped, are difficult for even “expert” human observers to tell apart.
- while packing a box with meat cuts, and then placing an external trade label on each box of meat, is uniform across the sector, each processor adopts a different approach to this task.
- Commercial off-the-shelf computer vision solutions are currently not sufficiently advanced to recognise individual cuts of meat, recognise the packing of meat into boxes nor able to adequately process external label data at production speed.
- Relatively inflexible positioning requirements for commercial off-the-shelf camera systems to ensure coordinate frame of the camera closely matches the coordinate frame of the label on box.
- Existing “smart” cameras need templates for each label type and pre-identification of label type as a box moves along a conveyor, requiring slowed production speeds.
- Existing “smart” cameras cannot translate Mandarin or other languages at production speed.
- Approach to engaging meat processors in research trials where they are required to answer questionnaire needs refinement.

In conclusion, the project revealed that there is still considerable effort required before a comprehensive, automated approach to box label verification can be delivered to the Australian red meat processing sector. Further work is required to train artificial intelligence models for primal meat type recognition and off-the-shelf industrial vision systems are currently inadequate to obtain all details contained in an external trade label. Standard industrial vision systems are unable to process foreign language translations. The project also provided directions for further research especially for development of an image search tool such that processors can quickly respond to any packing and labelling errors detected by overseas inspectors.

2.0 Introduction

The Australian red meat processing industry is the largest in the agriculture sector ($A28.5B in 2018-2019), is Australia’s largest Agricultural export industry ($A17.2B in 2018-2019), is the largest regional employer and the largest Australian manufacturing sector. In 2018-2019 the total sale of goods and services in the red meat and livestock sector was $72.5B (https://link.bondilabs.com/MLA-SoI).

The importance of meat export to the Australian economy was recognised in the 2020/2021 Budget announcement of $328M for Busting Congestion for Agricultural Exporters including $10.9M allocated for Building a More Competitive Meat Industry. A key component of the modernisation of meat processing will be identifying opportunities to improve regulatory activities such as developing electronic processes to replace paper-based forms, bringing in 'smart' technologies for agreed verification activities and doing away with manual processes and outdated technologies to bring in administrative efficiency.

One point along the red meat production chain, which is currently highly reliant on a combination of manual and automated processes (a "symphony of humans and machines working together"), involves the packing of meat into boxes for subsequent distribution. Correct selection (picking) and packing of pieces of meat into boxes by process workers, combined with placement of labels identifying box contents on the outside of boxes by automation, are critical stages in the processing of cattle into beef products (Figure 1).

Figure 1: Meat being packed into a carton

As a process which involves humans in the loop, for both packing and labelling of boxes is prone to error. These can have significant consequences for individual processors and the entire Australian meat processing industry. For example, in 2017, six Australian meat-processors who export to China were temporarily banned due to a labelling inconsistency caused by "Human Error" (https://link.bondilabs.com/aw2). The problem was identified as mismatch in inner and outer labelling on a small number of cartons (i.e. inner labelling on primal vacuum products did not match the outer labelling on the box).

The impact of such a temporary ban was extensive on the red meat industry including:

- Significant financial loss in the order of several million dollars.
- 'Some hundreds' of 'in-limbo' containers of red meat likely to be in transit to China, were caught-up in the suspension and re-exported to other markets, likely at lower value.
- Significant damage to Australia's reputation in China's export market.

The issue that emanated for this specific event in 2017 took several months to be resolved. In May 2020, a further ban impacted four Australian meat processors which combined make up 35% of Australian beef exports to China. A further two processors were blacklisted by China in the second half of 2020 (https://link.bondilabs.com/525799)

If this issue is not resolved, or at minimum labels are not automatically scanned for errors, it is feared that the same common labelling errors and subsequent export bans will continue. There have been many alternative solutions, such as RFID tagging of individual meat pieces and boxes, which may contribute to helping solve the labelling issues. However, the relatively high expense of high-frequency labels means an RFID approach is financially unrealistic. The research team was of the strong opinion that a computer vision-based solution is both less expensive than RFID to implement, as well as robust and agile enough to work in any processing environment as a last line of defence against label errors. The pharmaceuticals industry has already largely adopted computer vision label verification technologies with some significant success. The research team expects this same approach to label verification can be replicated into the meat processing environment.

In addition to label verification, using advanced AI computer vision techniques to analyse human "pick and place" tasks will help us answer the critical question "What cut of meat did a process worker pick and place into the box?" Amazon, Nespresso, and other logistics organisations have advanced the way in which artificial intelligence technologies are reducing inefficiencies in packing. This project will address the challenging problem of ensuring that process workers correctly identify, select and pack cuts of meat into a box. Combined with analysis of the information content and placement of box labels, our approach aims to significantly improve label verification in the red meat processing industry.

AMPC has previously supported research to explore the challenge to accurately verify that contents of a packed box of meat are accurately reflected in the external trade label box. Project 2021-1113 addressed whether it was possible to build machine vision tool using artificial intelligence (AI) to identify several primal meat cuts packed into a box combined with an optical character recognition (OCR) solution to verify that trade label accurately reflected box contents. This project explored development of an edge computing-based integrated OCR and AI model to identify six standard beef cuts and their corresponding trade labels, as well as a prototype label verification rig for implementation at a meat processing facility. The project revealed several major technical challenges that need to be addressed in the future development of a box label verification system, including:

1. Finding appropriate camera technology to capture intricate details of trade labels on rapidly moving boxes.
2. Managing the operation of electronic equipment in harsh production settings like boning rooms, even when using IP67-rated casings.
3. Obtaining a large enough visual training dataset for AI model development, enabling the model to recognize all primal meat cuts across various meat processing facilities.
4. Considering the cost and time required for training AI models.

5. Automatically recognizing and translating Mandarin character strings.

6. Offering real-time notifications for industrial control adjustments concerning boxes identified with label verification problems.

To address these issues, the current project explored commercial off-the-shelf (COTS), computer vision solutions from a range of vendors of industrial automation, sensing and control systems (e.g. for use in pharmaceutical, food & beverage, consumer goods manufacture). The aim of this project was to test whether a COTS label verification solution could solve the challenge in a meat processing context and at production speed.

During the project there have been increasing indications that processors previously banned from market access into China will be re-admitted during 2023. China is a significant market for Australian beef exports, with China importing over $1 billion worth of Australian beef in 2020 alone. It is therefore critical for Australian meat processors to ensure that their products meet Chinese regulatory requirements, including accurate labelling. Adopting a label verification solution can help ensure that labels are accurately applied and reduce the risk of export bans, thereby maintaining access to this important market.

3.0 Project Objectives

The objectives of this project were as follows:

3.1 Consult industry about their direct needs for label verification

This project started from the perspective that box label verification is important for Australian meat processors because it ensures accuracy and consistency in the labelling of meat products that are being shipped to customers, both domestically and internationally. Product labels are therefore a crucial part of ensuring product quality and safety, especially for red meat products. These labels provide information on a range of factors, including the product's origin, processing and packing date, expiry date, nutritional information, and potential allergens.

The project aimed to further interrogate the meat processing industry to better understand the need for a label verification system and to gauge interest in adopting such a system into their operations.

3.2 Conduct staged comparative experiments of existing off the shelf solutions which could solve the issue.

Previous research had identified that it is possible to adopt artificial intelligence vision technology to recognise individual cuts of meat. The purpose of this project was to explore whether one or more commercial vendors of industrial computer vision systems could demonstrate whether their technology could be applied to box label verification.

Following discussions with several vendors, we identified three, SICK, Omron and Cognex who provide computer vision solutions which could be applied to the problem. These vendors were provided with a set of requirements for a box label verification system and were subsequently offered the opportunity to demonstrate their responses to representatives from the meat processing sector.

Recordings of each demonstration, including a series of survey questions, were then distributed to the meat processing industry for evaluation.

3.3 Field trial at least one label verification system which has passed prior evaluation steps.

Based on the comparative evaluation of vendor responses to the challenge of demonstrating a box label verification solution, the project aimed to conduct a field trial of at least one solution in a meat processing facility. The aim of this was to identify any challenges in the integration of a COTS industrial vision-based box label verification tool into a meat processing facility and to evaluate effectiveness of the tool to identify cuts of meat packed into a box and to verify against data printed on the external box trade label.

3.4 Conduct staged experiments of “What was put in the box” computer vision solution to detect meat cuts placed into a carton

The purpose of this objective was to characterise the task of packing meat into boxes and then pursue a systematic approach development of an artificial intelligence vision system to detect and count objects as they are packed into a box. In this this objective aimed to explore whether a commercial vendor could supply an AI vision system for detecting what gets packed in the box.

3.5 Field trial prototype of “What was put in the box” computer vision solution in a meat processing facility that links with a label verification system.

Based on successful development of a “what gets packed in the box” system, the aim of this objective was to trial deployment of the solution into a meat processing facility and to integrate with the COTS box label verification solution identified for deployment into facility.

4.0 Methodology

Video Calls and Site Tours

Multiple video conference calls were conducted with all participants who initially responded to the Expression of Interest (EOI). In some cases, separate calls were organized with relevant people in the organization who had specific expertise e.g., Separate calls with microbiological QA staff, and then the QA team who monitor carton label quality. These 60-minute discussions via phone call or video chat were designed to:

- Understand their business challenges, focusing on food safety, inspection, and compliance.
- Communicate how to enhance the job decision-making intelligent vision technologies for carton label verification.
- Communicate how to continue to pilot the vision camera in a business.
- Begin to understand the technology readiness of their business to support vision-based verification solutions
- Deeply understand the carton label checking challenge within the industry.

Multiple site tours were also conducted during this time. The purpose of these site tours was to continue investigative work, and visually see areas where computer vision cameras may be set up in the future observing individuals performing carton checking jobs.

Additionally, interviews were conducted based on five separate research questions. Each interview was performed via video meeting and lasted around sixty minutes. Notes and comments from interviews can be found in Appendix 4 of this report.

Deep Learning Training Data Collection:

Multiple site tours were conducted to prepare equipment to capture images required to train deep learning models for Part 1 and Part 2 of this project. These site tours involved discussions with plant staff about how to best install data capture equipment (cameras) to record data for multiple hours across multiple days.

Technology Readiness (IT and Wi-Fi checks):

Due to the restricted nature of the project in picking a key processor to work closely with, there was a need to quickly identify those who might be able to adopt intelligent vision technologies now vs those who may need networking upgrades to their facility. Bondi Labs has previously been working with the participating project organisations and has this IT information readily available. However, the introduction of new computer vision cameras has created a need to revisit the technology readiness.

Vendor Demonstrations

The research team engaged several vendors of industrial automation and control solutions for this project. Three separate vendors were identified (Omron, SICK, and Cognex) who provided assurance that they could respond to a project brief (Appendix 3) detailing the requirements for a box label verification solution. Each vendor was then invited to provide a technical demonstration and/or on-site demonstrations of their computer vision label solutions. The following summaries outline each vendor that will participate in the project. Each vendor demonstration session enabled the vendors and key participant organisations to discuss the problem use case, as well as observe some of the vendor's equipment and operation in action.

Recordings of each vendor demonstration was made available for review by members of the meat processing community via the Screencast.com website. Each video contained embedded survey questions at the before and after viewing the demonstration from each vendor:

Pre-viewing questions:

Which meat processor do you represent?

What is your role in the organisation?

Has your organisation ever experienced market access difficulties as a consequence of labelling issues?

Can you provide an estimate of your daily production of boxes?

What roles in your organisation are involved in label verification (as many as required)?

Can you provide an estimate of the number of boxes currently checked, per day, for label verification?

Post-viewing questions:

What roles in your organisation are involved in label verification (as many as required)?

Can you provide an estimate of the number of boxes currently checked, per day, for label verification?

Did the vendor convey they understood the importance of label verification for meat processors?

How clearly did the vendor provide justification for their approach to label verification

Did the vendor describe how they would work with you to integrate their solution into your production system?

How confident are you that the vendor's solution can meet your label verification needs?

What was missing from the vendor's solution?

Would you be interested in participating in an onsite field trial of the demonstrated solution?

If a field trial was successful, would your organisation invest in a solution like this?

What is your expectation of the cost for a label verification system?

Any further observations?

An email was developed in collaboration with marketing and communications at AMPC (Caitlin Morris) and a mass email sent to several Hubspot mailing lists late September 2022. Content of the email as follows:

We'd like your feedback on box label verification solutions

AMPC has engaged Bondi Labs to understand the challenges to export resulting from errors in box packing and labelling. In particular, Bondi Labs are exploring ways to measure information content printed on external carton labels as well as automatically classify meat cut types packed into cartons using machine vision technology.

We are investing in a project that is looking at a box label verification tool that can automatically compare and contrast label information with meat type identification and provide an alert signal for instances where inconsistencies are identified. Bondi Labs has identified three vendors of industrial automation and machine vision solutions who have developed prototype solutions for review by the industry.

Each vendor has demonstrated its prototypes which have been recorded and will be shared with the broader red meat processing industry for feedback.

Please watch each video and answer the embedded survey questions in order to determine which solutions are of interest to industry.

1. Introduction to the project (3 mins)
2. Omron demonstration (18mins)
3. ASX/Cognex demonstration (33mins)
4. SICK demonstration (28 mins)

If you have any questions about the box label verification project, solutions, or survey questions, please contact Bondi Labs Research Manager, Dr Stuart Smith stu.smith@bondilabs.com

Links to each demonstration can be found in green above.

Vendors

Omron

https://www.omron.com.au/

Omron is a Japanese industrial electronics company with a product range spanning healthcare, industrial automation, power distribution in oil & gas and access control systems. The organisation has a global presence, and its Australia office is based out of Mt Waverly, VIC. Omron has a range of industrial computer vision camera sensors and systems and has applied experience providing solutions for food processing including meat. The Mt Waverly office will be the basis for any off-site lab demonstrations, as they have an in-house simulated conveyor system and camera sensor hardware.

SICK

https://www.sick.com/au/en/

SICK AG is a German manufacturer of sensors and sensor solutions. Their product mostly focuses on vision, capacitive, magnetic, opto-electronic and light sensors e.g., RFID readers, through to computer vision solutions. The organisation has offices around the world and is based in Australia out of Heidelberg, VIC. Sick has extensive experience providing industrial sensor and computer vision solutions to manufacturing, and food processing including meat. The Heidelberg office will be the focus of any off-site lab demonstrations, as they have an in-house simulated conveyor system and easy access to the broad range of their products.

Cognex (supplied by ACS)

https://www.cognex.com/en-au

https://www.asconline.com.au/

Cognex is an American manufacturer of machine vision, sensors, and software systems. The organisation is represented in Australia by Automation Systems and Controls (ACS), based in Bayswater, VIC. Cognex solutions are used globally and seen as one of the market leaders when it comes to vision systems has experience delivering computer vision systems to a range of logistics, manufacturing and food processing organisations in Australia including meat. The Bayswater office will be the basis for any off-site lab demonstrations of the technology.

Cognex is also proposing to install a camera system as a part of this trial into the JBS Brooklyn plant. The quote/specifications of this are still being determined.

5.0 Project Outcomes

The author should outline the outcomes from the project. This section should also include the key data sets with appropriate statistical analysis. The use of graphs and tables to summarise data is strongly encouraged. All project data should be included as an Appendix or supplied electronically.

Consult industry about needs for box verification:

This project started from the perspective that box label verification is important for Australian meat processors because it ensures accuracy and consistency in the labelling of meat products that are being shipped to customers, both domestically and internationally. Product labels are therefore a crucial part of ensuring product quality and safety, especially for red meat products. These labels provide information on a range of factors, including the product's origin, processing and packing date, expiry date, nutritional information, and potential allergens.

Product labels also help customers make informed decisions about what they are buying. For example, consumers can use the information on a red meat product label to check that it meets their dietary requirements, to identify the source of the product and to ensure that the product is free from any allergens or other harmful substances or that the products contained were processed according to religious or cultural requirements, e.g. halal.

In the context of red meat processing, accurate labels are also essential for tracking and tracing the product from the point of origin through to the end consumer. This is particularly important for export markets, where strict regulations often require detailed product information and traceability systems to ensure that products meet specific quality and safety standards.

Effective box label verification was therefore identified by the meat processing industry as crucial to maintaining accurate and consistent labelling across all meat products. It ensures that the product is accurately identified and that the correct labelling is applied to the exterior of each box, providing assurance that the meat product has been prepared in a safe and traceable manner. Ultimately, accurate labelling helps to protect the reputation of the industry, the integrity of the supply chain, and the health and safety of consumers.

The following provides a summary of the kinds of issues with box labelling identified by industry partners.

Label Problems:

- **misidentifying meat and entering in wrong data or making an error into label machine or applying the wrong label**
    - Net Weight
    - The category is written in cipher matching with AUS-Meat or cut items
    - Refrigeration statement e.g. "keep frozen"
    - Choosing the number of pieces
        - The user enters 2 pieces instead of hitting 20 into the label-making computer.
        - The user doesn't see a piece hidden under another thus the count is wrong.
        - User for some reason doesn't count correctly
    - Choosing the product type when entering into the label printing computer
    - Carton with meat-type already attached has user put the wrong piece in.
    - Miss classification by the user e.g. (Minor) Cube Roll entered as Chunk Role, (Major) Cube roll incorrectly entered as T-Bone.
    - Inner piece missing label altogether.

  - Carton label check job is to check each label complies with the expected standard. Standard can be found from AUSMEAT guidance and handbooks. But looking up a reference to this standard is hard and takes time.
  - Customers may also make additional requirement requests adding to the details on a label increasing difficulty in reading the label.
  - Incorrect language translation
- **label template details incorrectly entered**
  - Company name
  - Generic description
  - Cut description
  - Country of origin
  - Establishment number
  - Australian Inspected AI stamp
  - Packaging date
  - Marks required by an overseas customer
  - Label inserts mismatch with carton label details

- **Machine / Label print and placement**
  - The label is misprinted or damaged or covered by strapping
  - Label printer SKU is out of sync causing all cartons to be 1-2 production types behind i.e. 15 cartons of chunk roll than 15 of T-Bone. During the changer over the computer didn't account for one extra carton of T-Bone, thus the run following with be miss labelled.
  - The label can either be printed or placed by a machine but sometimes this is put on by hand.
  - The inner label does not match outer
  - Cartons going out with no label
  - Machine runs out of ink
  - The image faded – cannot be read by a scanner

- **Foreign items found in carton on delivery**
  - Contaminants (hair, metal, gloves)
  - wrong cuts in carton
  - Incorrect count of cuts in carton
  - Wrong brands going out from the plant

Needs of a Box label Verification tool:

A label verification solution should aim to detect all of these issues with a high degree of precision and accuracy. It is also important that the solution alert or automatically push suspect cartons off a line into a secondary inspection point for human verification.

Whichever system is developed MUST be able to work in a production environment at production speed.

Specific comments regarding label verification.

ORG1: *"I know internally it is a concern- while I do not have direct access to all of the data relative to this problem, it is my understanding that we receive a number of complaints around things like contaminants (hair, metal) but the majority of complaints from clients seem to relate more to the BL problem- wrong cuts, incorrect count- even wrong brands going out from plant."*

ORG2:

"Errors in labelling

- Image faded – cannot be read by a scanner

- Incorrect product described

- Inserts missing

- Label/inserts mismatch

- AI stamp or required text may not print onto label

- Inability to confirm translations on carton – Day to day check"

ORG3: *"With the present process we capture dozens a day- but this is not automated and it is dependent on humans, removing the dependency on the human element here would be a huge plus. We currently utilise the use scales operators for label verification. Another point here that should have great benefit is the language side of the label. We need to employ people who speak different languages to read and understand multiple labels going to many different countries. Of course, we select Chinese readers for Chinese labels etc., however some countries request bilingual labels, French, Chinese, German, Arabic, and Swiss- cause issues with employment all the time- we have difficulty enough getting good team members without having to find ones that are proficient readers of other languages. Regional dialect- overlap is usually enough with different dialects of the same or similar languages but can cause a potential problem if a specific importer asks for a specific dialect. Machine learning here again would be a huge plus."*

Can meat processing staff become confident and ready to utilise an automated label defect detection system?

Understanding how staff may come to use a new technology starts with understanding what they are doing now as well as the errors potentially being made. Engagement with the industry highlighted the following insights about the types of errors and reasons for errors being made during carton verification inspection.

Reasons for errors

- Humans get tired and looking at over 14K of cartons a day is a big ask.

- Those staff might look at 1% of those labels with the detail required

Per operator:

- Overall label compliance/per labelling station

- Details error list/operator/chain/product/who

- Pixel or image clarity report per printing station

- Tagging system that either kicks the carton off the main conveyor belt to a relabelling station where the details of the fault could be reviewed, and a label reapplied and sent back through the vision system or a visual assessment depending on the set-up and company's circumstances."

- Recorded data to assist with improved auditing situations.

- Currently, there are ergonomic issues with manual human label verification. Both eye strain, and muscular-skeletal issues with viewing and verifying cartons.

Need:

A solution ideally checks every single carton to relieve humans from inspecting and getting fatigued. This way, human intervention is reduced and can ensure full attention is given to cartons that do require inspection, rather than checking those which probably don't. Additionally, simple additions to label verification stations e.g. Large TV monitor displaying a camera feed of label and carton contents side by side would improve the ergonomic issues highlighted.

Adoption of Technology:

When asked about how workers may come to adopt a computer vision-based technology to assist in carton verification, some of the problems highlighted were.

- *"I don't think we actually know or understand how big the concern actually is."*

- *"How many clients receive better quality cuts or brands and don't say anything?"*

- *"I think everyone has resistance at first of automated systems until they realise it's a tool to help them with their role in the business"*

- *"I think it comes to staff selection and training."*

- *"Installation may struggle if there is not enough room for camera equipment e.g., how to get good viewing angle of carton or worker."*

- *"Market Access to places like China"*

Need:

These first-hand comments and feelings towards technology should be acknowledged and considered during the design phase of any project aiming to develop and deploy a human-computer interaction solution. Meeting the end-users need is vital to ensure the technology is used correctly and meets the desired objective. Additionally, it is even unclear to meat processors how much of an issue carton labelling errors are. The only feedback mechanisms are the limited internal auditing performed and customer complaints. It is feared that many more issues go unaccounted for. Therefore, a solution should record all cartons to allow for more rigorous internal auditing. Highlighting the benefits of a solution will go a long way in convincing organisations to invest and adopt these kinds of technologies. If a clear case is made that the risk of the export ban can be significantly decreased, then adoption may also increase.

Conduct staged comparative experiments of existing off the shelf solutions which could solve the issue.

Disappointingly, engagement with the demonstration videos by the meat processing industry was very poor. From original email out through to the 25th November 2022 only demonstrations by SICK (8 processors) and Omron (4 processors) have been viewed by industry participants. Of the total views, only Greenham provided pre- and post-video feedback for each vendor (Alistair Baker to be commended for his comprehensive engagement).

It was clear that the time commitment required to view demonstration videos and complete survey questions (60 minutes) was not suitable for the industry.

From a statistical perspective there is insufficient engagement by the industry to provide clear perspective on which of the vendor solutions were preferred.

Field trial at least one label verification system which has passed prior evaluation steps.

As a consequence of the poor feedback on the demonstration experiment a decision was made to pursue an in-processor trial of the vendor which best attempted to answer the Requirement document presented to all vendors. SICK provided the best attempt to demonstrate both a label and meat type identification system and was thus chosen to provide a field trial. For example, Figure 2 is a screen grab from SICK's presentation which indicated that they had the capability for training a network to analyse meat type.

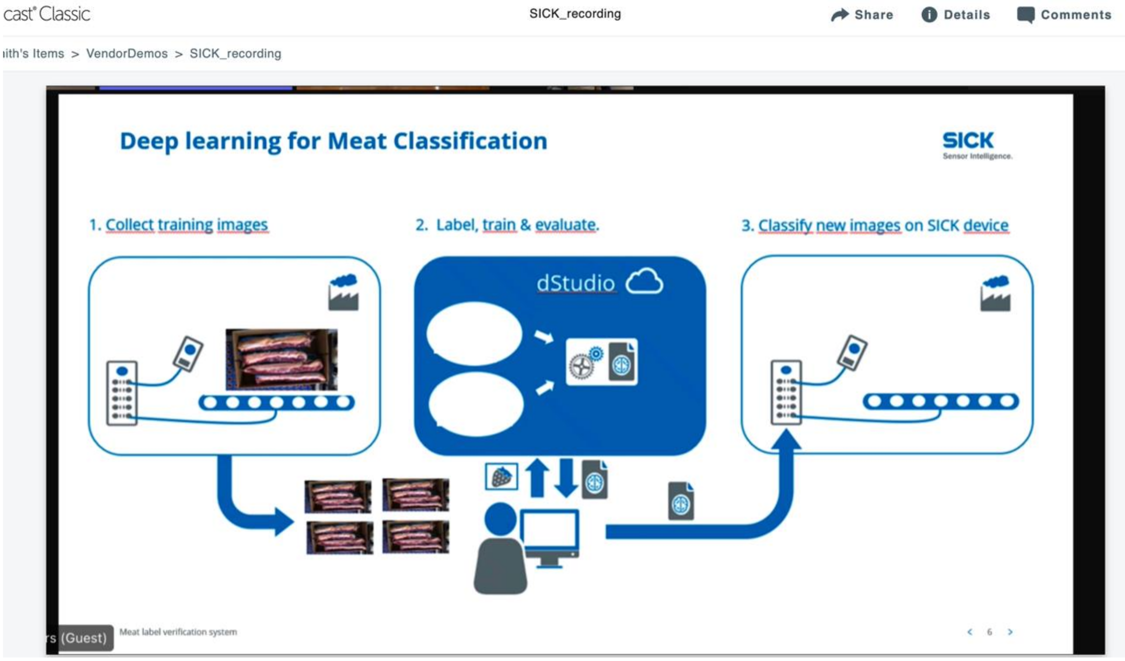


Fig 2. Screen shot from SICK presentation demonstrating their machine learning capabilities.

Figure 3 is a screen shot from the SICK presentation where they demonstrated that that their system could identify meat type in real-time. Their presentation highlighted that they had analysed 1000s of images of several cuts of meat (supplied by Bondi Labs) and that they had develop a machine learning model to discriminate those cuts and which could be loaded into their smart camera solution.

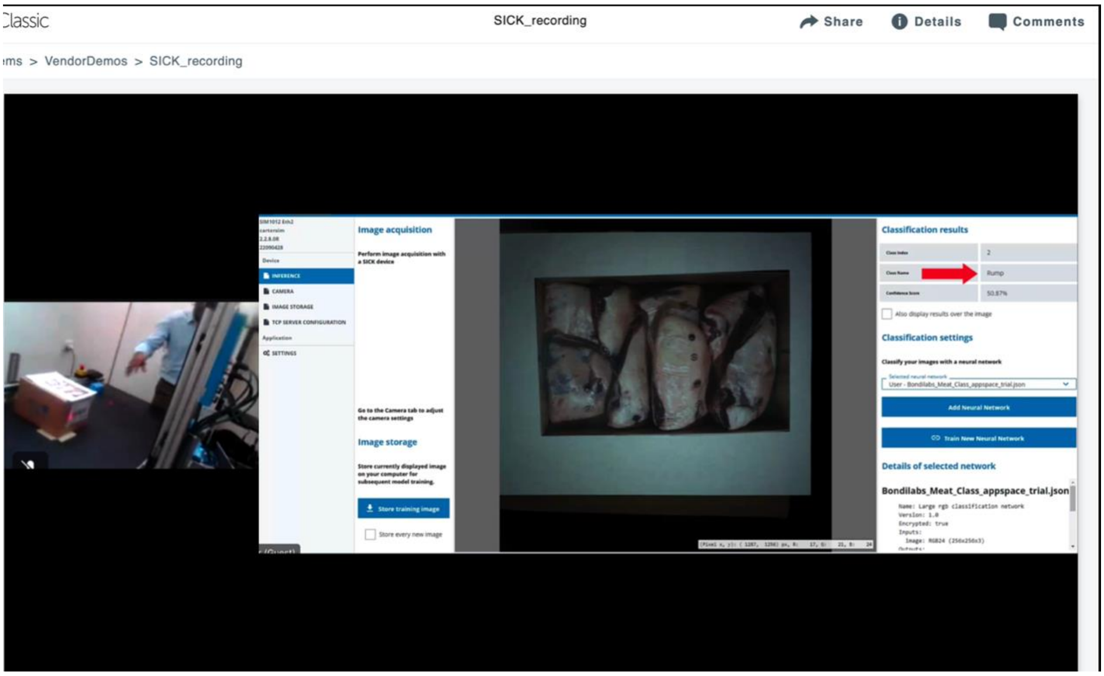


Fig 3. Screenshot from SICK presentation showing meat classification capability of their software. Their software shows analysis of a printed image of meat pieces (rump) packed into a box.

The Casino Food Cooperative expressed an interest in a trial of a box label verification solution and was chosen as the site for the in-processor trial of SICK's solution.

During October-November 2022 several visits to the Casino Food Coop site were made by the Bondi Labs team to better understand the challenges involved in deployment of a box label verification solution in their facility.

The aim of these visits was to identify the best location for the placement of label verification monitoring technology given the challenging environment of a meat processing facility (Figure 4). Following consultation with processor staff, it was decided that for the trial, to avoid complications associated with end-of-shift washdowns, the Quality Assurance room, located immediately before lids are applied to boxes, was best suited.

An additional aim of these site visits was to capture additional images of each of a number of different meat cuts. Interestingly, for several meat cuts, once they have been cryo-vacuum packed it was difficult for even expert observers to distinguish similarly shaped cuts (Figure 5).

Fig 4. Various potential locations for label verification trial at the Casino Coop from boning room through to QA room (bottom right)

Fig 5. Example showing the challenge of meat cut identification with increased uncertainty for some cuts of meat.

The project engaged with engineers and sales team at SICK to further refine the scope for work for the field trial. SICK provided access to all Bondi Labs and Casino team members involved in the project (Figure 6) and regular meetings were held via video conferencing to ensure project was kept on track.

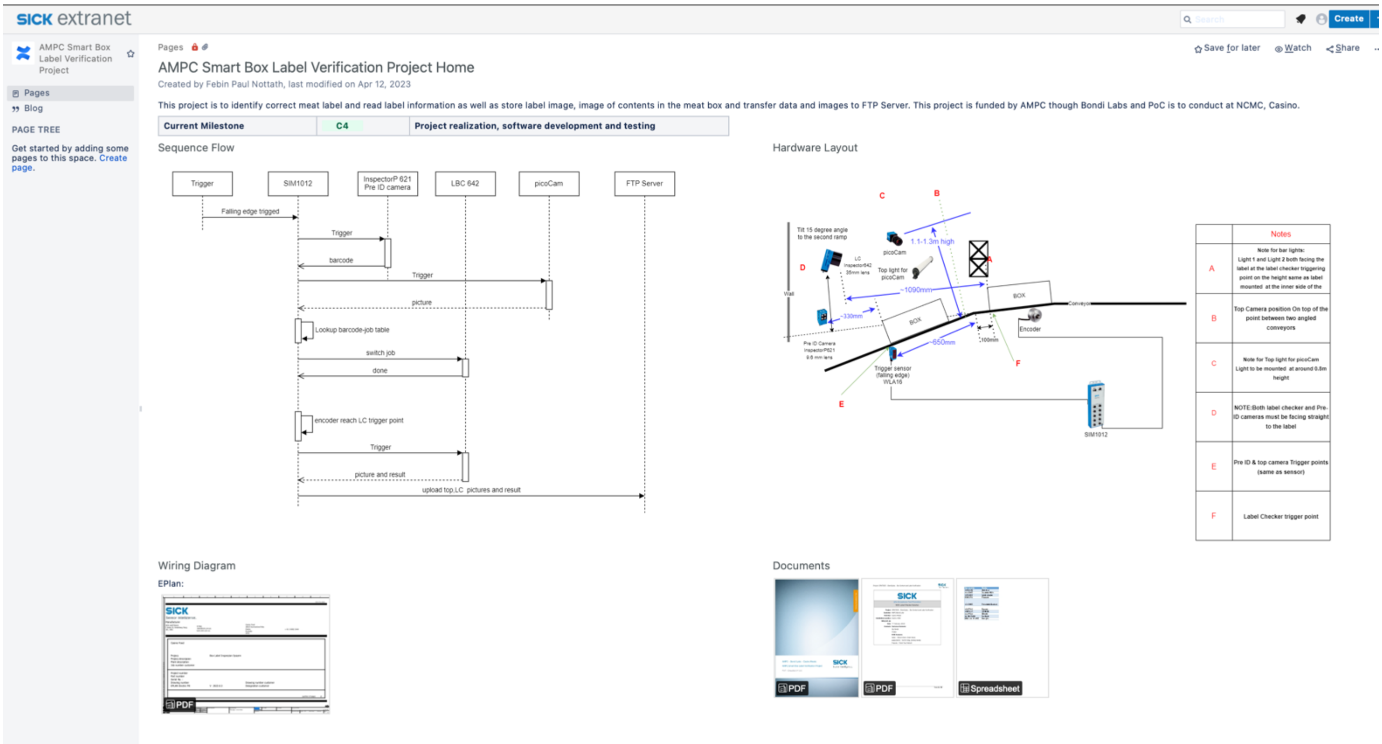


Fig 6. SICK Extranet for project management. All documents, diagrams etc related to the field trial were available to all project team.

The system suggested by SICK involves several components:

1. A label pre-identification camera (InspectorP621).
2. A label inspection camera (LBC642)
3. Box contents camera (PicoCam2 3mPx)
4. Trigger sensors
5. Sensor Integration machine (SID160Pro)
6. Illumination array
7. Rotary encoder

The camera system suggested by SICK (LBC642 and PicoCam2) are examples of “smart” industrial cameras designed for various industrial applications, such as factory automation, quality inspection, robotics, and logistics. These cameras come with built-in processing capabilities, allowing them to perform image analysis and make decisions based on the captured images without the need for an external processing unit. This can help streamline workflows, reduce system complexity, and improve overall efficiency.

Some common features of smart industrial cameras from SICK include:

- Integrated image processing: Smart cameras have built-in image processing capabilities, enabling them to perform tasks such as object recognition, measurement, and inspection directly on the camera.
- Easy configuration: Many smart cameras from SICK come with software interfaces allowing users to configure the camera and customize its functionality according to specific application requirements.
- Compact and rugged design: Smart cameras are designed to be compact and rugged, making them suitable for use in harsh industrial environments where space and durability are crucial factors.
- Versatile connectivity: Smart cameras typically offer various connectivity options, such as Ethernet, USB, or other industry-standard interfaces, making it easy to integrate them into existing systems.
- Real-time data processing: With their integrated processing capabilities, smart cameras can perform analysis on captured images in real-time, allowing for faster decision-making and reduced latency in industrial processes.
- Scalable solutions: SICK offers a range of smart cameras with varying levels of complexity and processing power, making it possible to select the most suitable solution for a given application.
- Pre-built algorithms and tools: Many smart cameras come with pre-built algorithms and tools for common industrial applications, such as pattern matching, code reading, and colour inspection, simplifying the setup process and reducing development time.

The logical flow for detection of labels and box contents is as follows:

1. System powered on and operational, conveyor running speed detected by rotary encoder
2. A box passes along the conveyor belt and is detected by a light sensor which triggers the system to capture images via logic built into the Sensor Integration Machine (SIM)
3. The SIM controller sends a signal to the label pre-identification camera which captures barcode of the external label and returns barcode data to the SIM

4. Based on the barcode, the SIM determines which kind of label is present (there are multiple label types) and then loads into the label inspection camera the appropriate “recipe” for identification of required components of the label.
5. The label inspection camera is then triggered to capture an image of the label and returns several pieces of information to the SIM:
    - Product number
    - Meat type
    - Barcode
6. The SIM also sends a trigger to the box contents camera and receives an image in return
7. Images of both label and box contents are displayed to an operator via display screen
8. Images and label data are stored in a folder for uploading to an image store server

One of the challenges encountered in preliminary design for the SICK system is the requirement for the coordinate frame of reference for the label camera to be as closely aligned with the frame of reference of the label on box as possible. Because of the placement of external trade labels on the trailing edge of the box as it moves along the conveyor belt in the QA room, there is a limited number of positions for mounting the label inspection camera. When an industrial image processing system is used to read trade labels on boxes (e.g., barcodes, QR codes, or text) from an oblique angle (Figure 7), several challenges may arise that can impact the system's performance and accuracy:

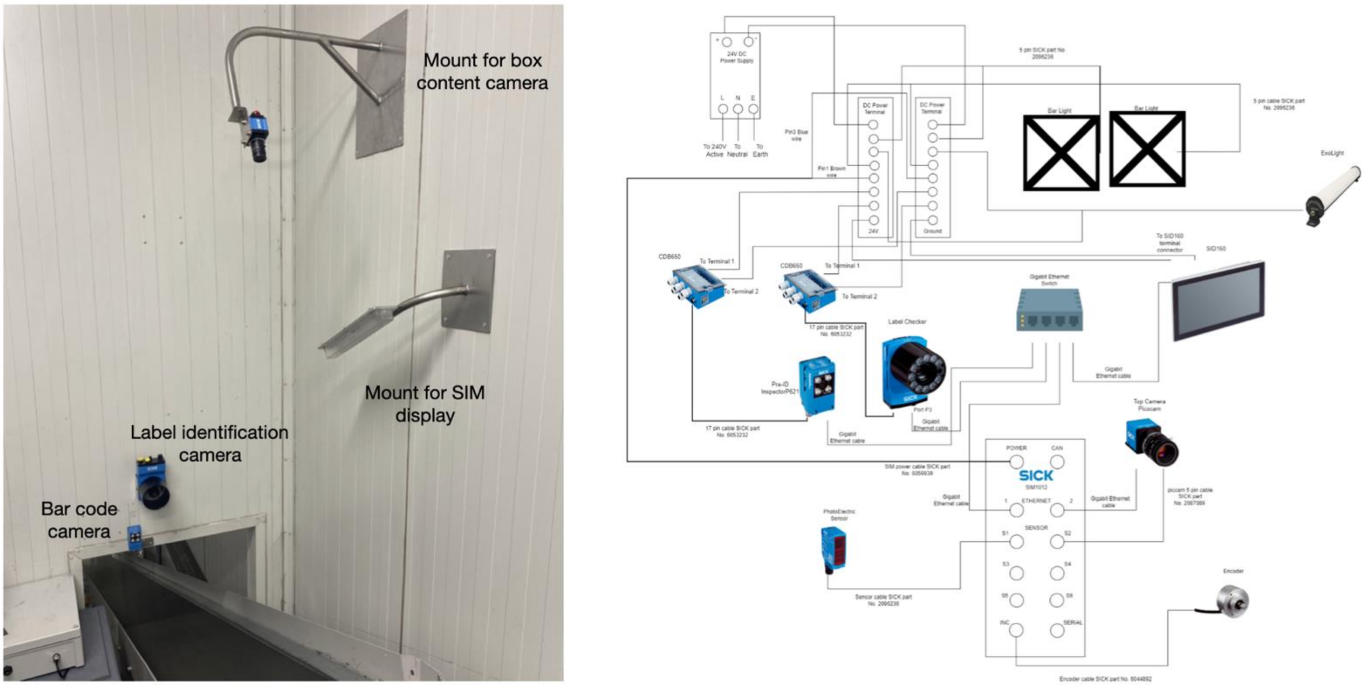
- Perspective distortion: An oblique angle can introduce perspective distortion, making the label appear skewed or warped in the captured image. This distortion can make it difficult for the image processing algorithm to accurately recognize and decode the information on the label.
- Reduced resolution: If the camera is at a highly oblique angle to the label, the effective resolution of the label in the captured image may be reduced. This can lead to a loss of detail and make it more challenging for the image processing algorithm to accurately read the label.
- Occlusion: In some cases, an oblique angle may cause parts of the label to be occluded by other objects or the box itself. Occlusion can make it difficult or impossible for the image processing algorithm to extract the necessary information from the label.
- Uneven illumination: The angle between the camera, the label, and the light source can cause uneven illumination, which may create shadows or reflections on the label surface. These lighting issues can negatively impact the image processing system's ability to accurately read the label.
- Depth of field: While depth of field might not be the primary issue in this scenario, it can still play a role. A shallow depth of field can result in parts of the label being out of focus, especially if the label surface is not perfectly flat or parallel to the camera's focal plane. An out-of-focus label can be challenging for the image processing algorithm to process accurately.

Fig 7. Impact of relative position of camera coordinate frame of reference to that of label on external surface of box of meat. Note the impact of defocussing of righthand side of image in B and the impact of lighting reflections in A.

To overcome these challenges, several measures can be taken:

- Adjust the camera angle and position to minimize perspective distortion and occlusion.
- Use a camera with a higher resolution sensor to capture more detail in the label, even when viewed from an oblique angle.
- Use a lens with a larger depth of field to ensure that the entire label is in focus, even if the surface is not perfectly flat or parallel to the camera's focal plane.
- Employ proper lighting techniques to minimize shadows and reflections on the label surface.
- Apply image pre-processing techniques (e.g., perspective correction, adaptive thresholding) to improve the quality of the input image before feeding it into the image processing algorithm.

Significant delays in supply chain limited the ability of the project to obtain necessary camera hardware for installation in Casino. Camera components were not shipped to Casino until March 2023. The engineering team at Casino have fabricated mounting fixtures for the cameras (Figure 8A) and, as of final report submission, we are awaiting final cabling of cameras to control computers (Figure 8B) and final commissioning by SICK engineers.



A B

Fig8. A: Location of cameras for label verification system in Quality Assurance room. B: wiring for the various components of the SICK box label verification solution.

Because of the delays in commissioning of the SICK system we have been unable to fine tune the arrangement of cameras and lighting to address issues of relative orientation of camera to box label as discussed above. We have also been able to assess whether the system as designed by SICK will operate according to specification at the very least, or whether it will be capable of reliably extracting “meat type” form external trade label for comparison against an AI model running on their PicoCam2 smart camera.

As a consequence, Bondi Labs has initiated development of an alternate box label verification solution which we aim to trial by June 2023. Rather than use “smart” camera technology to analyse labels and box contents at the edge of production, we are building a box label verification solution using best-in-class industrial camera technology (e.g. Teledyne Genie Figure 9) to capture label and box content images for immediate processing by a central AI and optical character recognition (OCR) server located on premise. The Teldyne Genie range of industrial cameras have been identified as providing superior high speed image acquisition performance that will be crucial for capturing high resolution, blur-free images of labels and box contents as boxes move along conveyor belts at production speed. In our modified design only two cameras are required in addition to trigger sensors and lighting. Rather than the need to load a predetermined label recipe into a (SICK) smart camera, these relatively “dumb”, but industry standard, cameras from Teledyne can connect via high speed ethernet ports to a central server where all image processing can be performed by OCR and AI algorithms.

Once the SICK camera system has been commissioned it is our intention to perform and comparison between this and the box label verification tool developed by Bondi Labs. It is expected that both the SICK system and a solution from Bondi Labs will be able to be compared by mid-2023.

Fig 9, Teledyne Genie industrial camera for comparison to SICK solution.

Conduct staged experiments of "What was put in the box" computer vision solution to detect meat cuts placed into a carton

The aim of this objective was to develop a computer vision solution that can watch a worker pick up a piece of meat, place it into a carton, and the result is saved to a computer system e.g. "4 pieces of cube roll put in carton"

What's in the Box (WITB) Prototype

In addition to the vendor demonstrations, we also explored how we can build an automated system for identification of what cuts of meat are packed into each box. At the Casino plant, primals are packed into boxes at several packing stations (Figure 10). At each station an operator will select an empty box from an overhead conveyor, place the box onto a packing platform then select relevant cuts of meat to fulfil the requirements for the shift. Once each box is packed, the operator initiates the printing of a label then applies the label to the box (Figure 10B). At time of packing the operator may notice that there has been a failure in the integrity of the vacuum seal on one or more bags. They will place a coloured sticker onto the piece for subsequent reworking by operators further along the production chain.

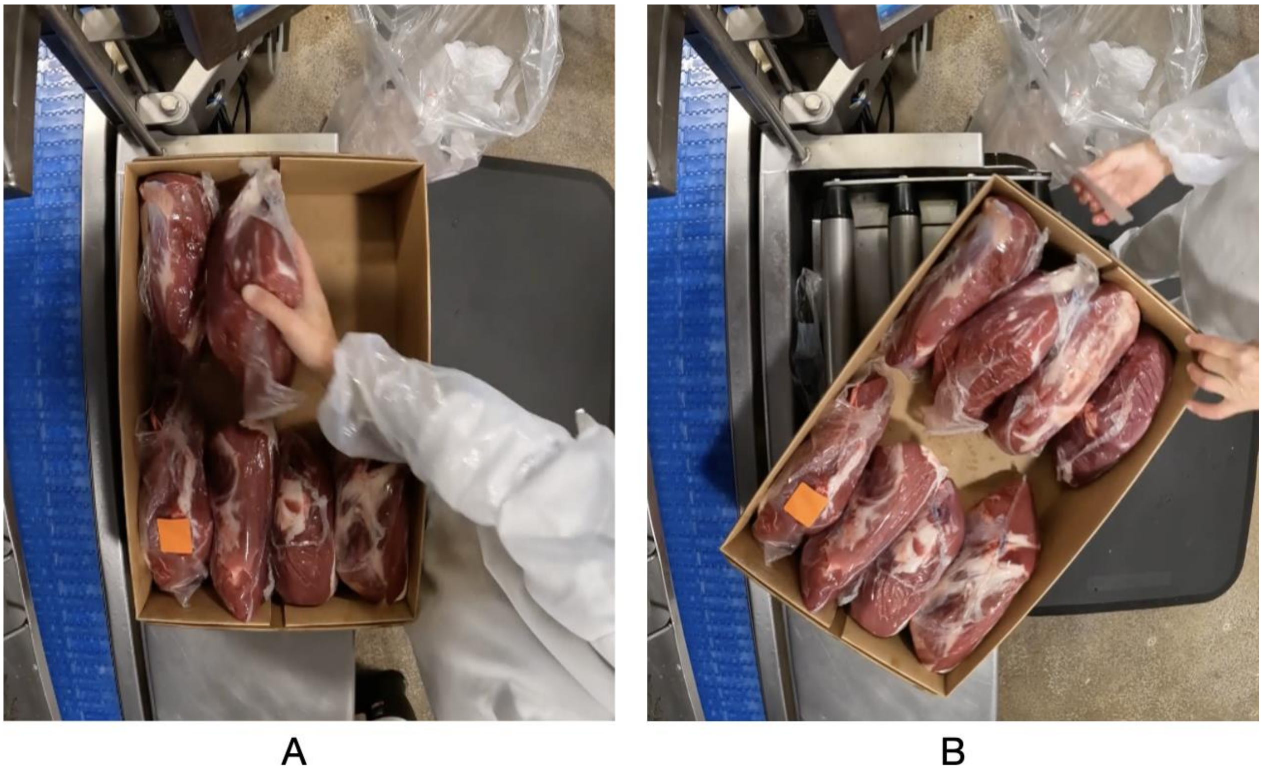


Fig. 10. (A) Shows packing of meat pieces selected from adjacent conveyor belt into a box and (B) application of label to external surface of the box. Note the orange sticker indicating a "leaker bag"

WITB Computer Vision System:

The "What is in the Box" computer vision system is compromised of an IP or networked camera device streaming footage to a central server. The central server runs computer vision tasks and displays the result to a web dashboard which can be viewed by an end user. This system has been designed to operate offline and within a private VPN located on premise (Figure 11).

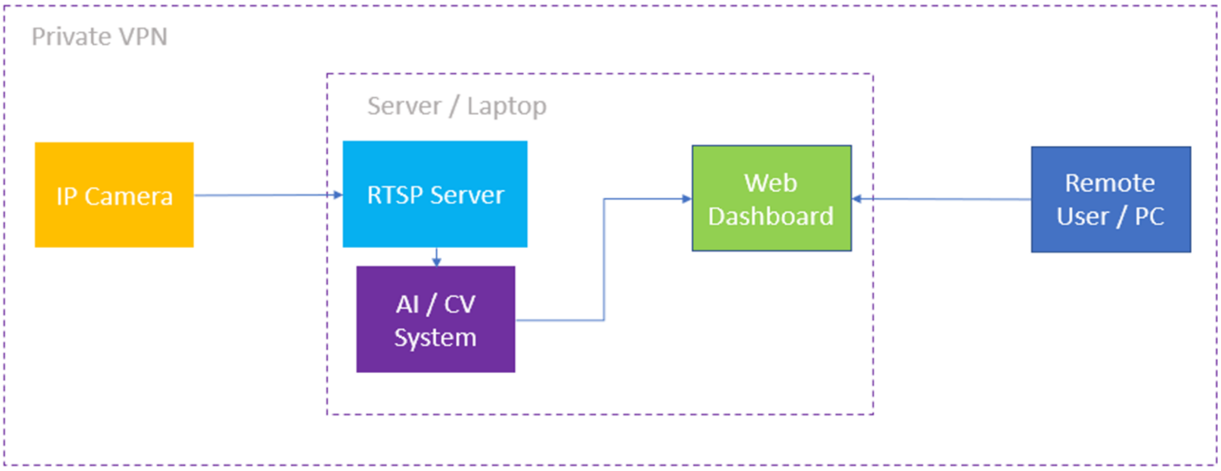


Fig 11. What's in the Box (WITB) computer vision system architecture.

Yolov5: Object Detection:

The object detection framework YOLOv5 chosen is a collection of compound-scaled object detection models trained on the COCO dataset. It is an evolution of the YOLOv4 framework (Bochkovskiy, Wang, Liao, 2020) originally based off the Darknet YOLO framework (Redmon, Divvala, Girshick, Farhadi, 2016). Yolov5 has been re-written and has added a number of useful features such as utility functions to ingest, export data streams, and use data augmentation during the model training phase. For the purposes of this small prototype, it is adequate but other object detection models could be used (see Figure 12). Yolov5 based solutions are now starting to make its way into agricultural research and commercial projects such as fruit defect detection (Yan, Fan, et, al, 2021; Yao, Zhang, et, at, 2021). The model has also been used to detect action/activity with people i.e., safety equipment detection (Zhou, Zhao, Nie, 2021).

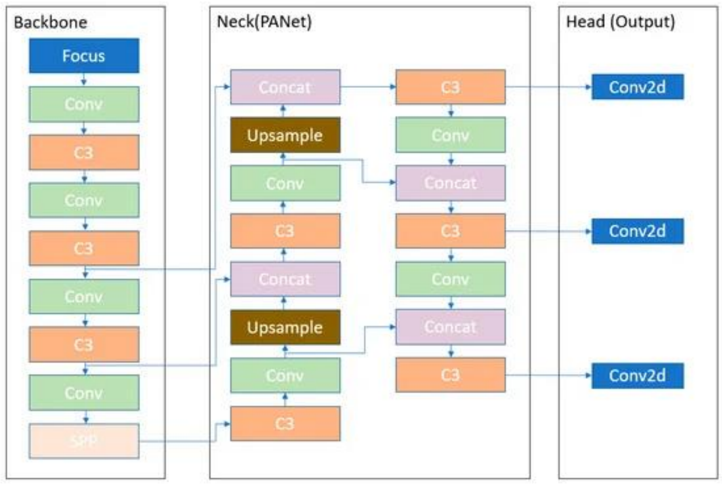


Fig 12: YOLOv5 Architecture (Nepal, Eslamiat, 2022)

Object Tracking: Strong Sort

A second step to the system is to track detected objects in a frame across time. This solution is using the StrongSort (Figure 13) framework (Du, Song, Yang, Zhao, 2022) which is an evolution of the original DeepSORT tracking architecture (Wojke, Bewley, Paulus, 2017). This allows detected meat, hands and cartons to be tracked over time and tracking data used to infer action and activity in the scene.

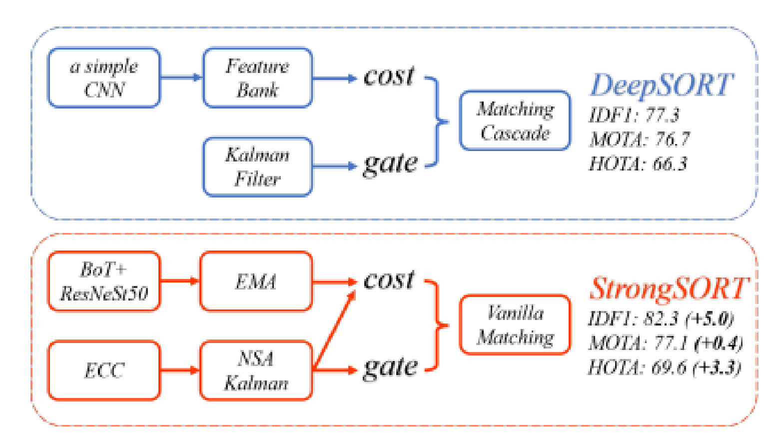


Fig 13: Framework and performance comparison between DeepSORT and StrongSORT. Performance is evaluated on the MOT17 validation set based on detections predicted by YOLOX (Du, Song, Yang, Zhao, 2022)

Computer Vision + Rules:

The system uses some additional custom code to create understanding of activity and action from the generated bounding boxes per frame.

To detect what cut of meat gets packed into the box we will test a system that aims to solve (Figure 14):

1. Detect new carton interaction on conveyer belt
2. Detect the type of meat cut being picked up placed into carton (handling removal of meat cut/mistake)
3. Detect a hand in the frame
4. Determine final itemised list of meat cuts put into carton
5. Detect if items are put in or put placed out of the carton.
6. Object Detect individual cuts of meat (6 types)
7. Send extracted data to other networked services
8. Collect enough data for a Deep Learning object detection model to detect up to 6 types of meat in cartons.
9. Clean-up and Annotate meat in carton data for model training
10. Model Training and Evaluation for 6 types of meat in cartons
11. Reporting dashboard should show an itemised list of items that have been placed in or out of the carton to a webpage.

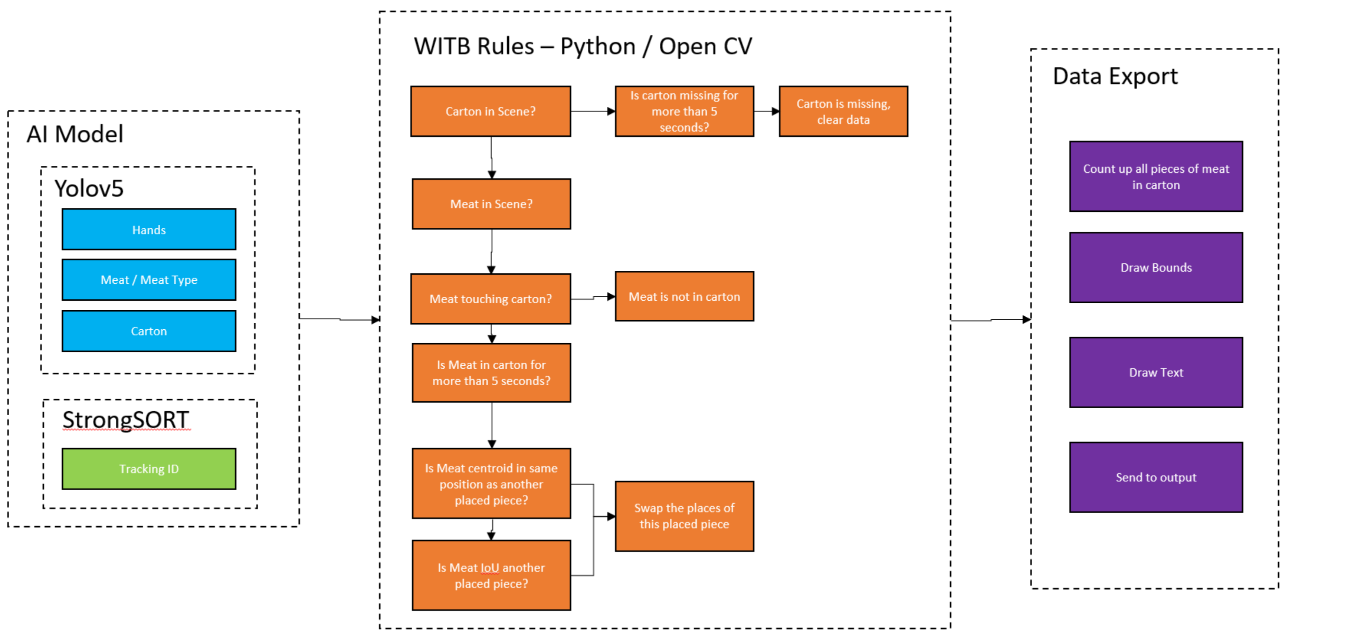


Fig 14: WITB Rules and Architecture

Data Collection & Annotation

During visits to the Casino facility, we have collected several hours of footage from a GoPro camera positioned directly above the packer station (Figure 15). We are in the process of correlating the time stamp for each video with the packing run sheet from these recording sessions which will enable us to annotate each image we extract from the videos for training an artificial neural network to undertake image recognition (see below). For image annotation we are using the Computer Vision Annotation Tool (CVAT) tool. CVAT is a free, open source, web-based image and video annotation tool which is used for labelling data for computer vision algorithms. Originally developed by Intel, CVAT is designed for use by a professional data annotation team, with a user interface optimized for computer vision annotation tasks.

Fig 15: GoPro Data capture rig.

Prototype Design

Following annotation and training of AI models we have initiated preliminary design of a "what gets packed into the box" proof of concept. We have now started to evaluate various models against data obtained from site visits to the Casino processor (Figure 16).

Fig 16: Meat, hands, carton being detected.

Annotated Images:

A few techniques were used to create a dataset large enough to train an object detection model. Over 7000 images were annotated for the following categories (see Table 1). Additionally, a synthetic dataset of 10,000 images was created for the meat types 1, 2, 4, 5, 6, 9, 10, 11 (Figure 17). A technique was used to quickly label class annotations by first training a model to detect meat in a scene. This model was then used in Auto annotation using CVAT to quickly annotate the remainder of the dataset. The dataset was carefully uploaded in tasks per known meat type i.e. a short video clip that will only contain meat type 1, or 2, or 4 etc. This way, when the dataset is exported out of CVAT we can run a script to apply an additional meat type class per detected meat. For example, if an image has 3 pieces of meat detected, and the image is named meat1_00123.jpg. Then we can insert an additional 3 annotations of meat1 into the annotation file. This plus auto annotation techniques dramatically increased the speed of data annotation (Table).

Table 1: Number of annotations per class instance (real and synthetic datasets)

Category	Real	Synthetic	Synth+Real
meat	24644	54268	78912
hand	11828	0	11828
meat2	9890	8077	17967
carton	6983	8649	15632
meat1	6722	8858	15580
meat11	2709	5278	7987
meat4	2316	7975	10291
meat10	883	2898	3781
meat5	774	7113	7887
meat9	687	7262	7949
meat6	663	6807	7470
	Real	Synthetic	Synth+Real
	68,099	117,185	185,284

Figure 17: Example of synthetic data generated

Object Detection Performance:

The model being used was trained on over 17,000 images (real and synthetic) on 10 different categories. Note, the "Meat" category is always the same / duplication of each meat type ID. Additionally due to difficulty in approving the names of the meat cuts, meat cut codes were used instead to help make the results robust. All trained categories had a meat Average Precision score of 90% or above (Table 2). The confusion matrix also demonstrates the categories do not get confused between other categories, however there is room for improvement (Figure 18).

Table 2: Object Detection Performance per category – scale is normalised 0.0 – 1.0

Re-Code	Detected Type	Images	Instances	Precision	Recall	mAP@.5	mAP@.95
Carton	carton	843	690	0.956	0.98	0.988	0.97
Striploin	meat1	843	633	0.986	0.959	0.99	0.925
Short Ribs	meat2	843	976	0.996	0.975	0.994	0.97
Bolar	meat4	843	237	0.983	0.97	0.967	0.935
Chuck	meat5	843	68	0.995	1	0.995	0.962
Oyster Blade	meat6	843	55	0.996	1	0.995	0.956
Brisket	meat9	843	61	0.959	0.984	0.961	0.897
Point End Brisket	meat10	843	82	0.975	0.965	0.97	0.911
Shank	meat11	843	275	0.974	0.969	0.983	0.911

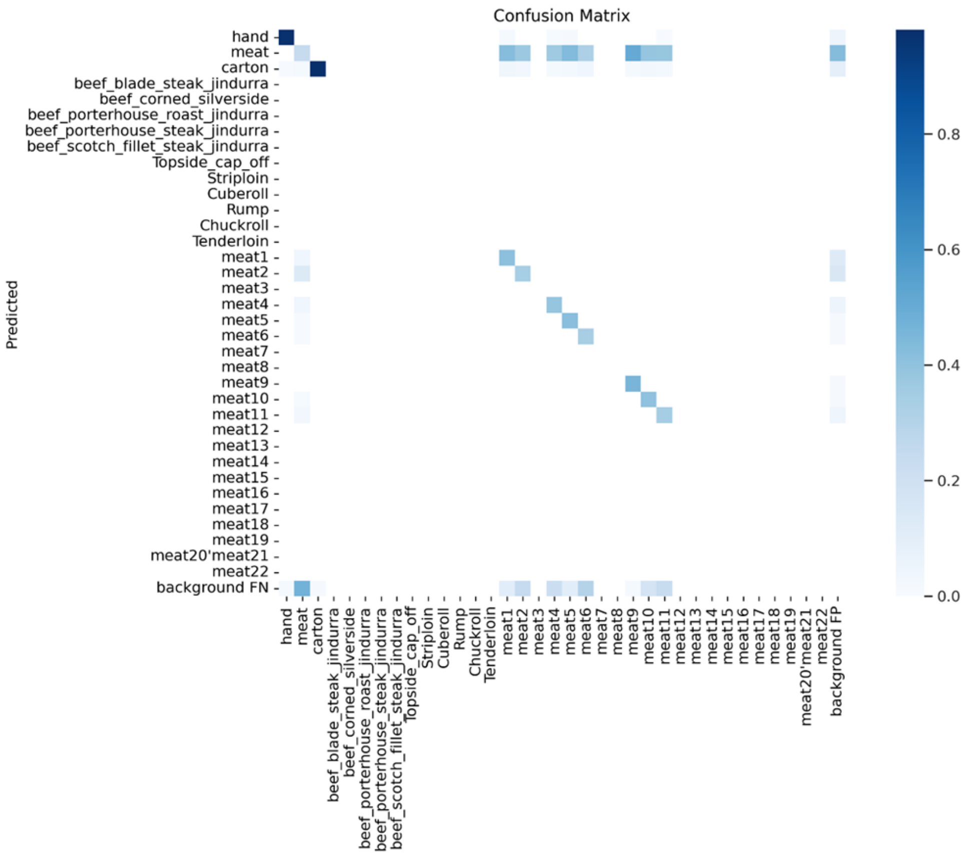


Fig 18: Confusion Matrix of trained categories.

Meat Cuts Detected in Action

The following images showcase each meat cut being detected as well as an estimate as to the number of meat pieces placed into the carton. In some cases, the meat cut count will include hidden pieces occluded i.e. placed underneath. The computer vision system has to deal with a few different stages of meat detection:

Carton and Hand Detection:

Object Detection model Provides a list of detected bounds and tracked ID's per bound depending on the class detected. Hand is detected and its interaction with the carton is detected using simple Axis Aligned Bounding Box (AABB) (Figure 19).

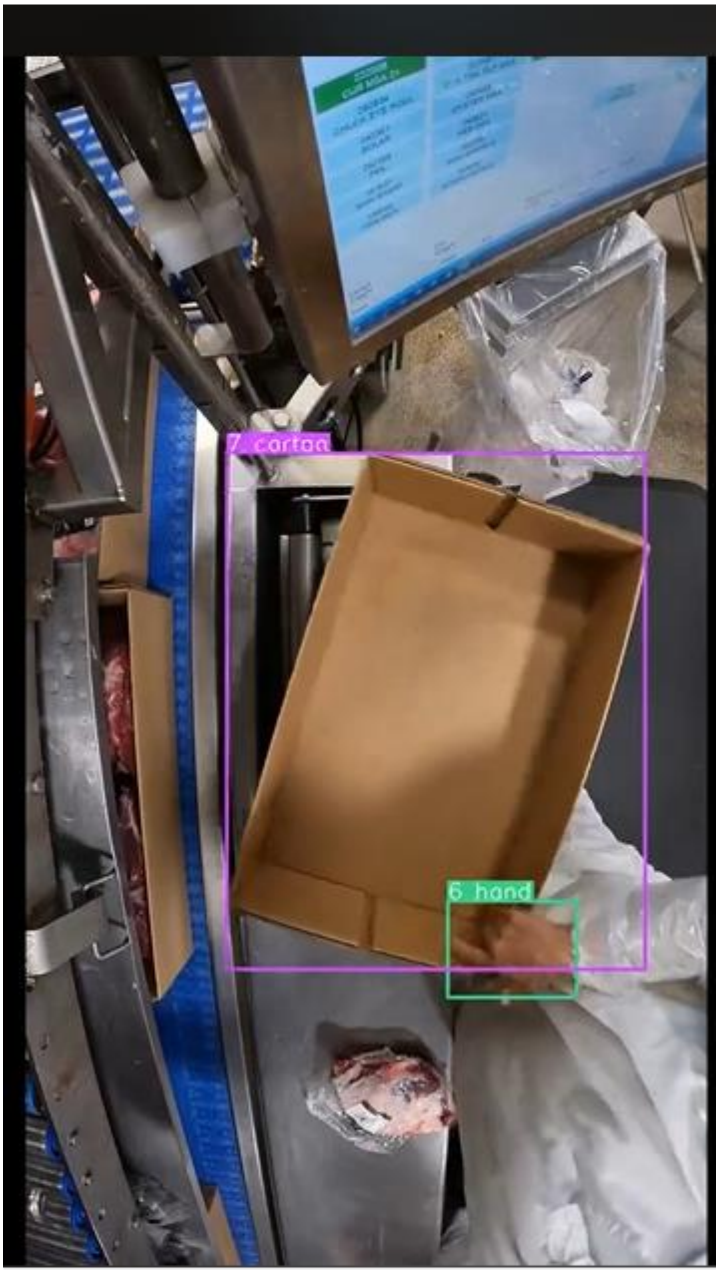


Figure 19: Carton and Hand detection

Meat Located outside of a carton: Yellow boarded meat.

Combination of AABB and determine if central point of a meat bounding box is located inside the bounds of the carton (Figure 20).

Fig 20: Meat Located outside Carton

Meat Found in the carton but still moving: Light blue boarder.

Combination of AABB and determine if central point of a meat bounding box is located inside the bounds of the carton (Figure 21).

Fig 21: Meat Found in the Carton but not stationary

Meat definitely in the carton and stationery: Dark Blue boarder.

Each meat ID has a timer attached to itself as well as the motion of the object. If the time of the meat is greater than 5seconds, we class this as meat that has been placed inside the carton (Figure 22).

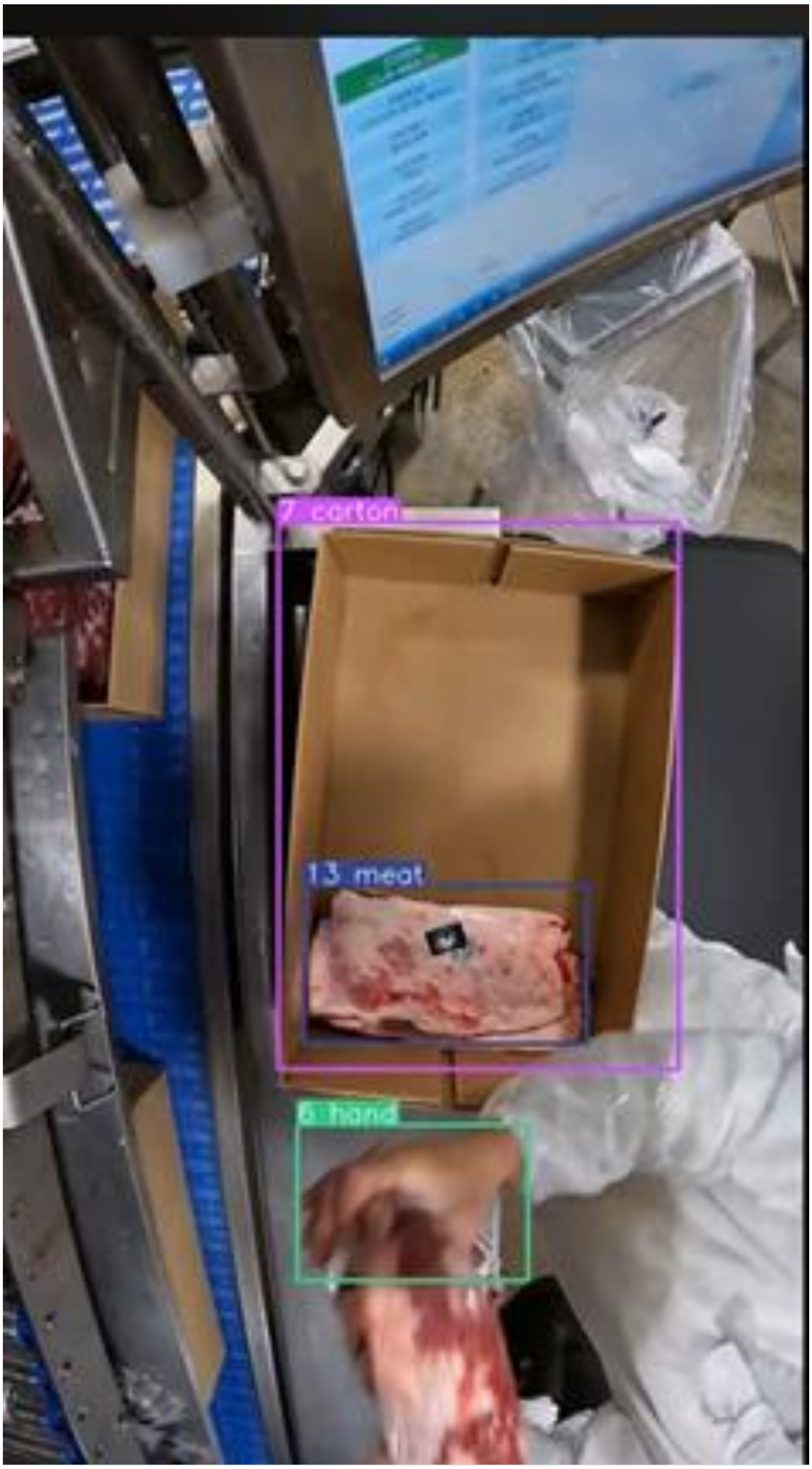


Fig 22: Meat stationary inside the carton

Overlapping meat:

Meat often is placed on top of another piece of meat. Obscuring the originally tracked bounding box. We measure the difference in central point and bounds using Intersection Over Union (IoU) to determine if we predict a piece of meat is being obscured by a new piece of meat. If so, we add to the count, other wise we treat this as a tracking ID switch due to instability in the object tracking system (Figure 23).

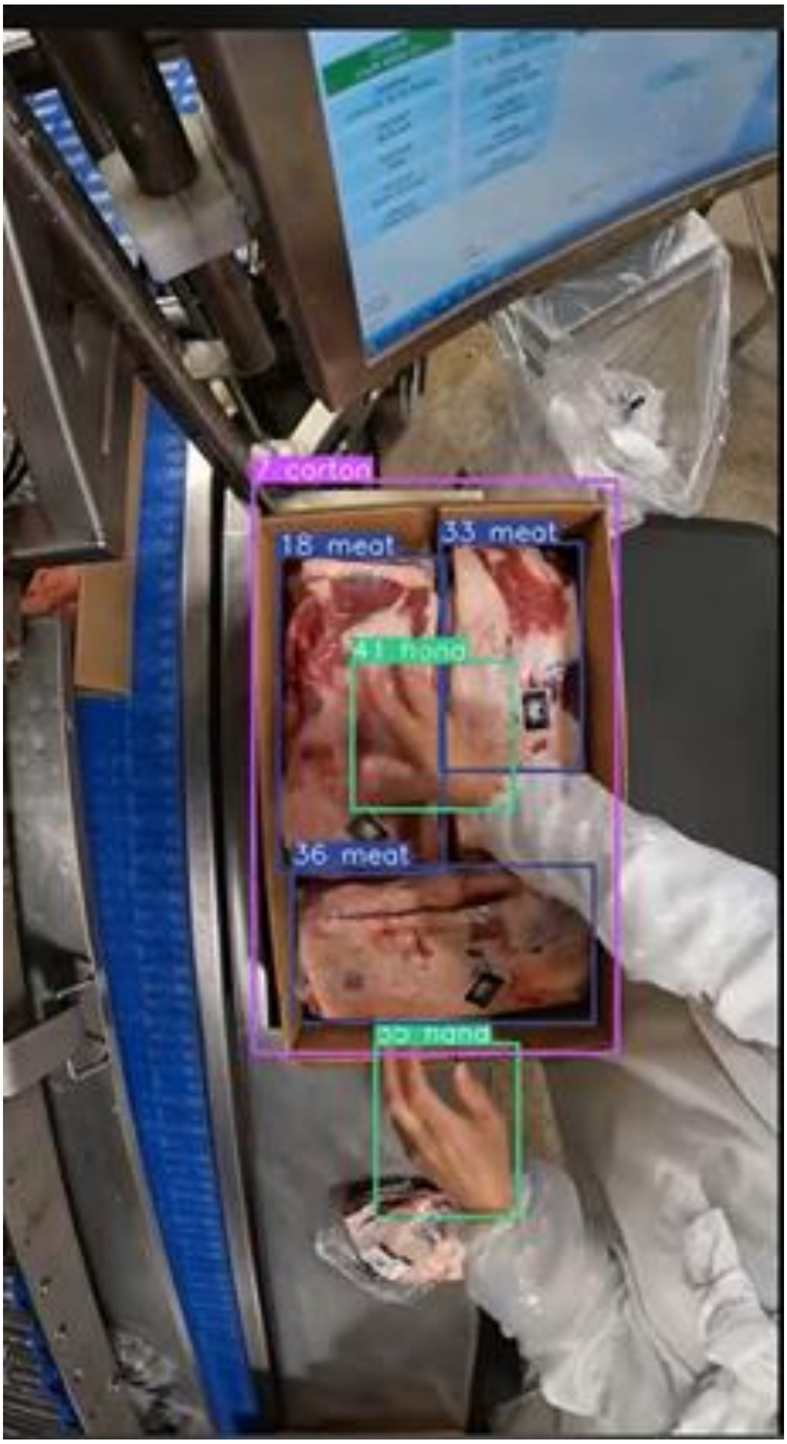


Fig 23: Overlapping Meat

Meat Losing tracking ID:

Poorly trained models may struggle to keep track of pieces of meat and change the tracking ID. E.g. light blue boarder is showing a new piece of meat appeared even though it never actually was passed into the carton. This is an example of a tracking ID switching (Figure 24).

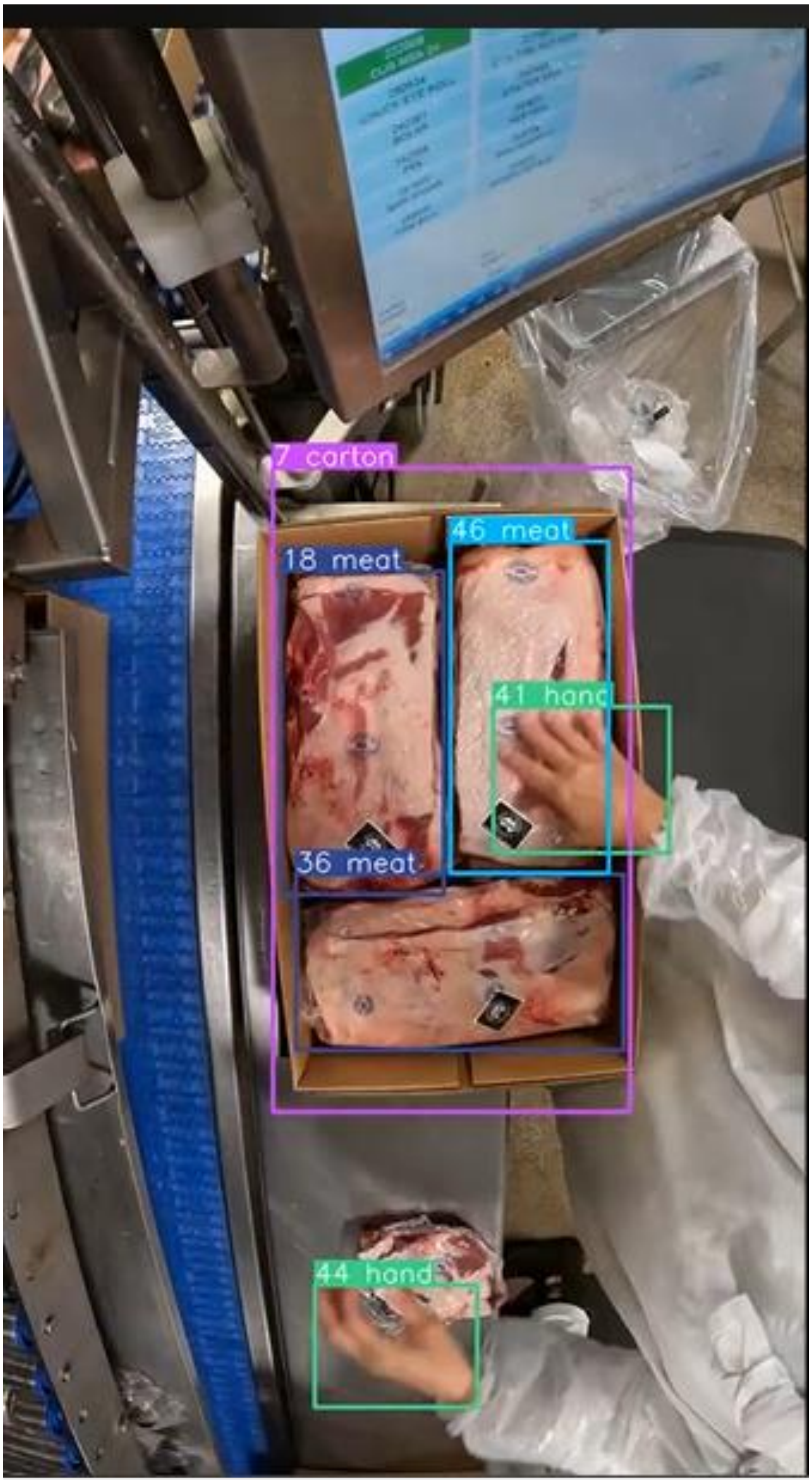
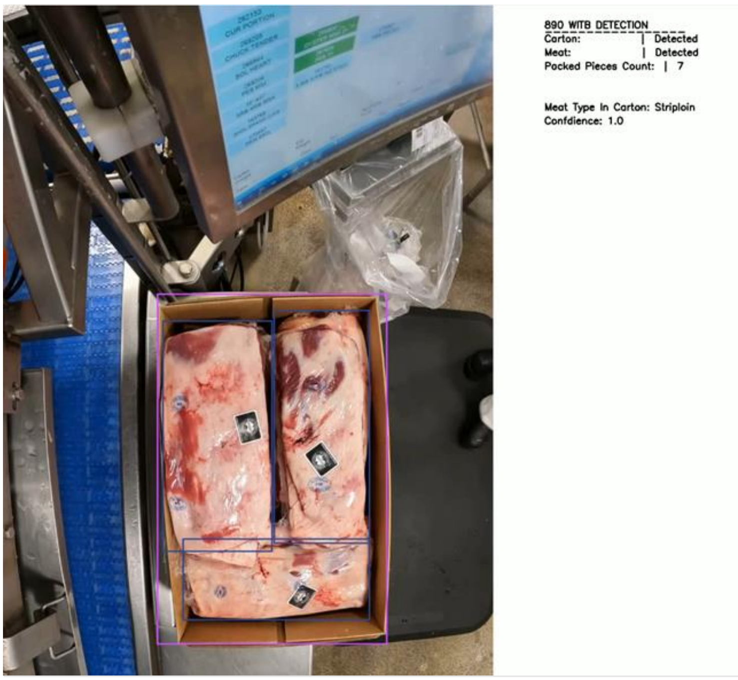


Fig 24: Meat Losing Tracking ID

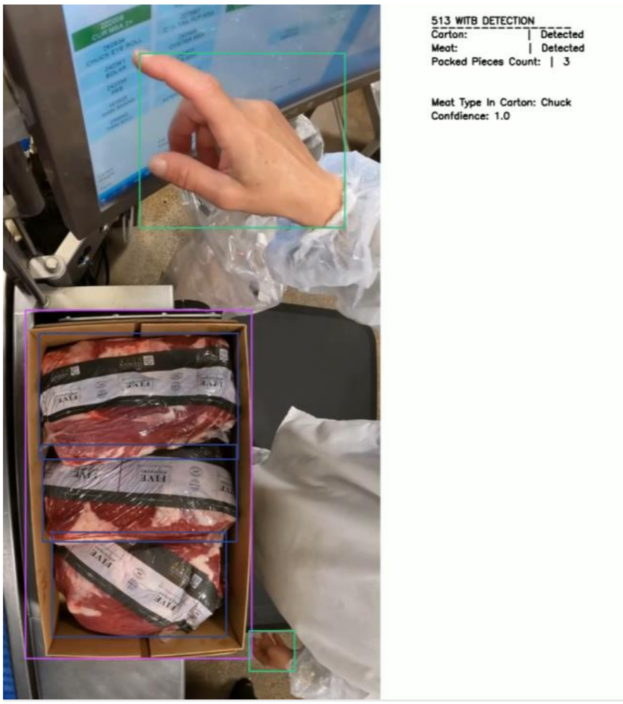
Meat types detected.

It took a significant amount of time to get the vendors to the point where they were prepared to deliver a demonstration of their solution to the box label verification problem. At completion of each demonstration, we were disappointed that none of the vendors provided a complete box label verification solution that incorporated meat type identification with label information extraction. Of the three, only SICK provided confidence that they had adequately responded to the requirements document. As such we resorted to developing our own approach to this issue. The following provides examples of the range of meat types we have trained an AI model for at the box packing station.

Striploin:



Chuck:



Web Dashboard

A basic web dashboard will be tested in the field to showcase the detection system working. It was designed to be flexible and configurable for field testing purposes. The dashboard displays the video stream with relevant detection information printed to the screen (Figure 33).

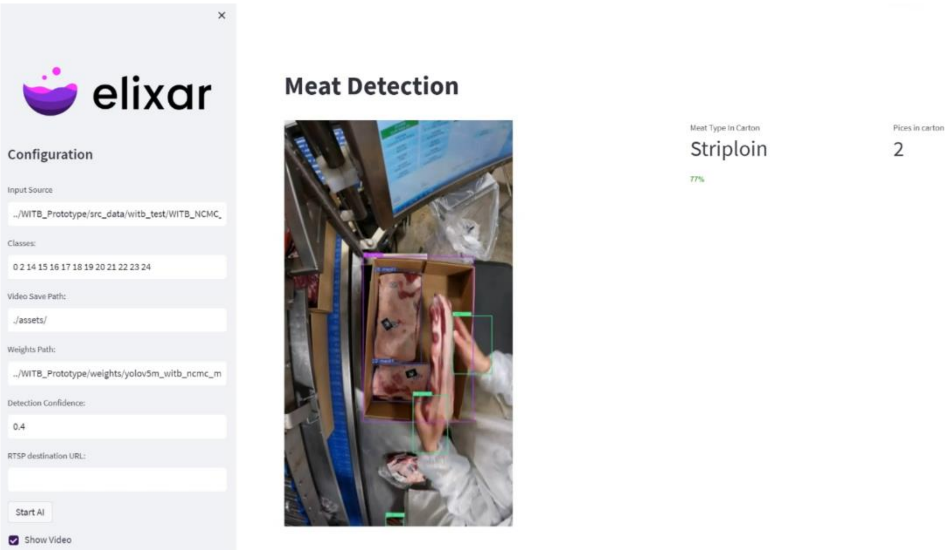


Fig 33: WITB We dashboard

Field trial prototype of “What was put in the box” computer vision solution in a meat processing facility that links with a label verification system.

Due to the delay in delivery of the SICK box label verification solution, the project was unable to explore integration with the What was put in the box solution.

6.0 Discussion

Some of the key challenges faced during this project phase are.

Engagement process with Vendors

It took a significant amount of time to get the vendors to the point where they were prepared to deliver a demonstration of their solution to the box label verification problem. At completion of each demonstration, we were disappointed that none of the vendors provided a complete box label verification solution that incorporated meat type identification with label information extraction. Of the three, only SICK provided confidence that they had adequately responded to the requirements document.

Engagement by meat processors with vendor demonstration

Disappointingly, engagement with the demonstration videos by the meat processing industry has been very poor. From original email out through to the 25th November only demonstrations by SICK (8 processors) and Omron (4 processors) have been viewed by industry participants. Of the total views, only Greenham provided pre- and post-video feedback for each vendor (Alistair Baker to be commended for his comprehensive engagement).

Hardware shortage (Global Chip Crisis)

Due to the unforeseen labour and transport constraints caused by COVID, the manufacturing of computer chips is creating major delays in high-end electronics equipment. All camera sensor vendors have expressed that there is a risk some hardware may not be available to use during this project due to the global chip shortage. The research team has discussed with camera vendors that for at least the off-site lab demonstrations, all camera equipment and systems will be available to showcase. Once a solution scope is developed with the meat processing participant organisations, the research team will determine which camera vendors are in a position to deploy equipment before or after the project testing phase (post-Sept, 2022).

The aim of this project was to test whether a commercial, off-the-shelf label verification solution could solve the challenge of human-errors in the packing and labelling of boxes of. In attempting to address this significant challenge for the meat processing sector, this project has revealed major limitations including:

1. Relatively inflexible positioning requirements for COTS camera systems to ensure coordinate frame of the camera closely matches the coordinate frame of the label on box.
2. Lighting is an important determinant of the success or failure of a camera-based automated quality assurance system
3. So too is choice of lens, especially regarding maintaining focus through a suitable depth of field
4. OCR in “smart” cameras need templates for each label type and pre-identification of label type as a box moves along a conveyor, requiring slowed production speeds.
5. Existing OCR technology in vendor cameras cannot translate foreign languages “on-the-fly”.

6. While all vendors claimed to be capable of providing AI support, none had a pretrained model for meat type identification

Additionally, during the research it was discovered that key areas for concern are dealing with both domestic and overseas complaints but having limited data on hand to respond to any customer complaints or queries about shipments. While the processors we engaged in discussion revealed that they will take photos of consignments of meat, they have no systematic way of storing those photos for quickly providing evidence of the carton/label issue matching with shipment consignment. Making this data easily searchable at a moment's notice seems to be an opportunity to investigate further. If this solution did exist, it could then easily be extended to help create further marketing value. For example, a potential customer could view in close to real time, images of the product they are about to purchase, therefore adding an additional opportunity to enhance the market reputation of the product and organisation.

Further exploration of the impact of errors in labelling revealed occurrence of product shrinkage. High shrinkage costs in manufacturing refer to the financial losses incurred by a company when products are mislabelled or incorrectly categorised, leading to a lower perceived value and ultimately lost revenue. This phenomenon is particularly prevalent when a higher-quality product is mistakenly labelled as lower-quality, causing it to be sold at a lower price point than it should be.

There are several factors that contribute to high shrinkage costs in this context:

- Miscommunication: In a complex manufacturing process, communication breakdowns between various departments (design, production, quality control, marketing, and sales) can lead to the mislabelling of products. This can result in a high-quality product being labelled as lower-quality, and vice versa.
- Human error: Mistakes can happen at any stage of the manufacturing process, and human errors may lead to the incorrect categorization of products. This can be due to oversight, lack of training, or simply mistakes in data entry.
- Inadequate quality control: If a company's quality control processes are insufficient or ineffective, it may be difficult to accurately assess the quality of a product. As a result, higher-quality products may be misidentified as lower-quality ones, leading to lost revenue opportunities.
- Complexity of product specifications: When a product has numerous specifications, it can be challenging to accurately label and categorize each unit. This can result in the inadvertent mislabelling of higher-quality products as lower-quality ones.

To prevent high shrinkage costs, manufacturers should invest in robust quality control processes, employee training, and effective communication channels. Additionally, implementing technology such as automation and AI can help minimize human errors and improve the accuracy of product labelling and categorisation.

7.0 Conclusions / Recommendations

Since these attempts to address box label verification, there are now strong indications that processors previously banned from market access into China will be re-admitted during 2023. There is therefore an urgency to ensure

Australian red meat processors can maintain market. Despite an improvement in the price and availability of cattle, shortages in staff also represent a major limitation for the Australian meat processors to take full advantage of the renewed interest by China. If relatively untrained staff are deployed into packing and labelling operations, the incidence of box label errors can only be expected to increase. Development of unified automated box label verification solution therefore remains a high priority for the Australian red meat processing industry, \

A box label verification tool that captures images of both the external trade label and the contents of a box of meat offers various opportunities for reducing the impact of shrinkage as well as improving efficiency, traceability, and quality control in the industry. Some of these opportunities include:

- Enhanced traceability: By capturing images of both the external trade label and the meat contents, this tool can improve traceability throughout the supply chain. This will enable easier identification of the source of the meat, lot numbers, and other relevant information in case of recalls or food safety concerns.
- Quality control: The tool can help ensure that the meat products match the information on the trade label, aiding in quality control efforts. Images of the contents can also help detect any visual defects, damage, or spoilage, enabling quick corrective action.
- Inventory management: The box search tool can facilitate efficient inventory management by providing accurate information about the contents of each box. This can help reduce waste and improve stock rotation, ultimately leading to cost savings.
- Streamlining logistics: By providing accurate information about box contents, the tool can help streamline logistics operations, including shipping, receiving, and storage. This can lead to reduced errors and faster processing times, increasing overall efficiency in the supply chain.
- Data analytics: The captured images and associated data can be used for advanced analytics, helping identify trends and patterns in meat quality, supplier performance, and consumer preferences. This can aid in informed decision-making, targeted marketing, and product development.
- Compliance and regulation: The box search tool can help ensure compliance with industry regulations and standards by providing a reliable way to document and verify product information. This can reduce the risk of non-compliance penalties and enhance the company's reputation.
- Consumer trust: By improving traceability, quality control, and compliance, the tool can contribute to increased consumer trust in the meat products and the brand. This can lead to higher customer satisfaction and loyalty.

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9.0 Appendices

9.1 Appendix 1. User personas

Carton Checker:

Overview

Name: Jeremy Baits

Role: Carton Checker

Age: 31

Shift Length: 7.6 hours

Education: Cert in Meat Processing

Location: Ballarat

Bio: Jeremy has been working at the meat works for the last 6 years. He started in the boning room and has moved around to different areas of the meat works over the years. Recently he completed some initial meat processing, product specification and hygiene courses and is looking to get into the QA department.
He has taken on a new role in performing carton checking and verification.

"I need to keep up and check all the boxes. So many boxes"

Responsibilities:

Visually searching the carton label and the carton contents.

Using hands to move carton contents around to count pieces and check if inner label is present.

Checking carton label matches export specification

Reporting issues found

Role + Tasks + Goals

As a	I want to	So that
Carton Checker	Visually compare all carton labels and inner contents	I can ensure our carton labels are error free.
Untitled	Become alerted to label inconsistancies	I can make a judgment call if I should flag this as an issue.
Untitled		

Core Needs

- See carton contents and label side by side to make a comparison
- Identify all carton label issues
- Be alerted to potential hard-to-spot label inconsistencies
- Log into the computer if a major carton labelling issue is found.

Pain Points:

- Visual inspection can be mentally draining work
- Need to be able to recognise different cuts of meat inside a box.
- Some label issues are really hard to see under time pressure
- Often having to check specification sheet (5-15 pages) to check export standards - Can't read foreign text
- Often changing product runs means every couple of minutes a change in carton label spec.
- Distracted and fatigued towards the end of shift, end of the week, leading up to a holiday break.
- Potentially having 1500 cartons pass in front of them a shift. Difficult to check them all effectively.
- Doing the job for multiple hours a day - Not a lot of room to move around
- Having to switch tasks (Look at carton side, move around to look at carton contents and remember carton values).

Extra:

Training received in product specification course where you learn what a cut piece looks like and how it meets product standards.

QA Manager

Overview

Name: John Simmons

Role: QA manager

Age: 52

Education: Certificate in HACCP process management, Cert in Meat Processing **Location**: Ballarat

Bio: John has been working at the meatworks for the last 25 years. He started in the boning room and has moved around to different areas of the meatworks over the years. He has been performing QA Management for the last 5 years and would like to eventually move up into a group management role.

Role + Tasks + Goals

As a	I want to	So that
Scrap Metal Inspecto	**Incoming and outgoing of scrap metal - Initial check on the cargo storage of oiliness, corrosion, suitability of cargo storage, metal type, presence of non-metallic objects, radiation, weight of cargo (incoming and uploading), explosive substances.**	To handle the initial checking on exports and imports shipments in order to proceed with next steps of inspections.
Untitled	**Visual inspection of containers and empty holds for their cleanliness and suitability for scrap transportation**	To ensure the suitability of scrap metal sites for imports and exports.
Untitled	**Visual control of the loading process and sampling of scrap**	Use of handheld equipment to instantly analyse the scrap metal sample instantly
Untitled	**Laboratory analyses of scrap metal quality - Major use of analytical equipment**	Use of different types of handheld equipment to analyze the scrap metal samples collected.
Untitled	**Photo and video report.**	Provide photo and video evidences of inspection
Untitled	**Certifications**	Certify the quality of the material in accord with standard quality of HS Codes

"I need to be confident our export cartons won'tat the border."

Responsibilities:

- Performing QA monitoring and verification inspection on meat workers, the facility and machines. This covers many areas of the plant, not just carton checking.
- Regarding carton checking, need to ensure operating standards are being upheld and all carton labels are error-free.
- Occasionally need to step in and perform carton checking role due to poor staff training or short-staffed.

Extra:

Work a 7.6-hour day but may often do overtime to ensure things are prepared before a shift or reports are done after a shift.

Pain Points:

- Hard to have eyes on everyone at all times.
- Hard to find the time to review issues found.
- Hard to react in real-time to issues.
- Hard to collect data needed for reports.

Core Needs

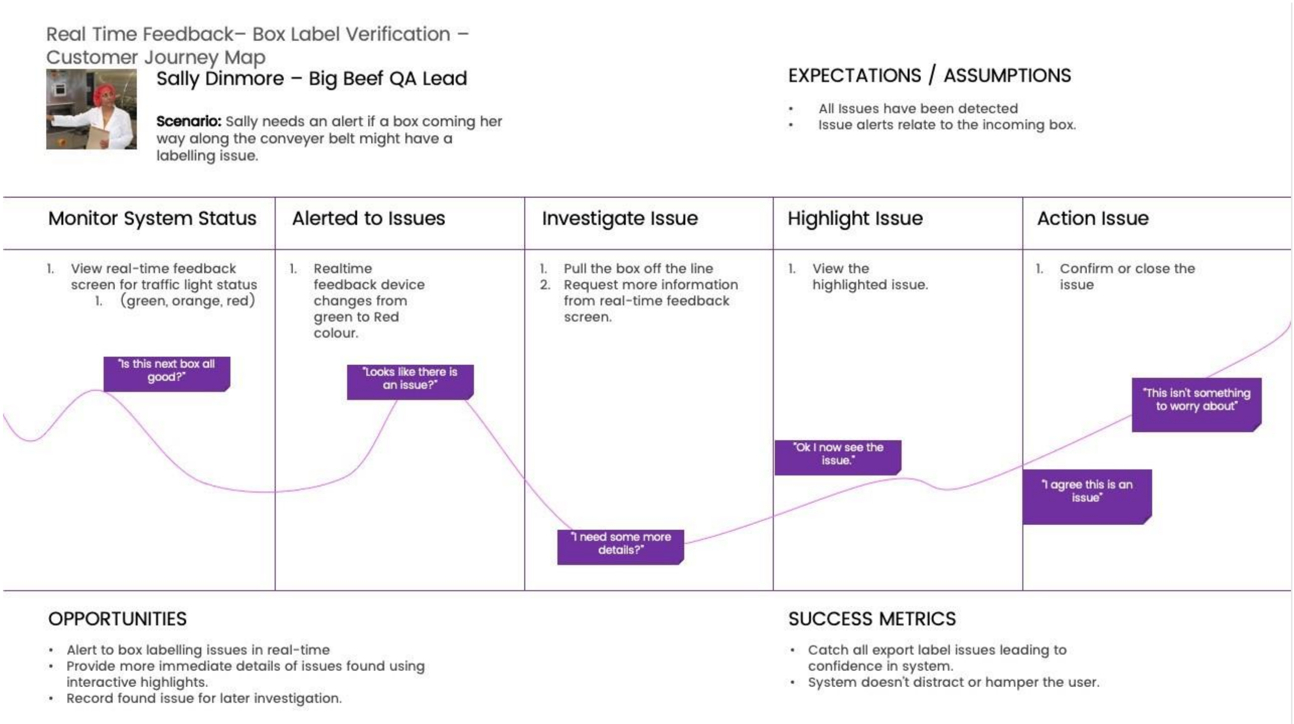
- Quick snapshot that the cartons are error-free.
- Easily view and review found carton label issues.

9.2 Appendix 2 Customer Journey Map

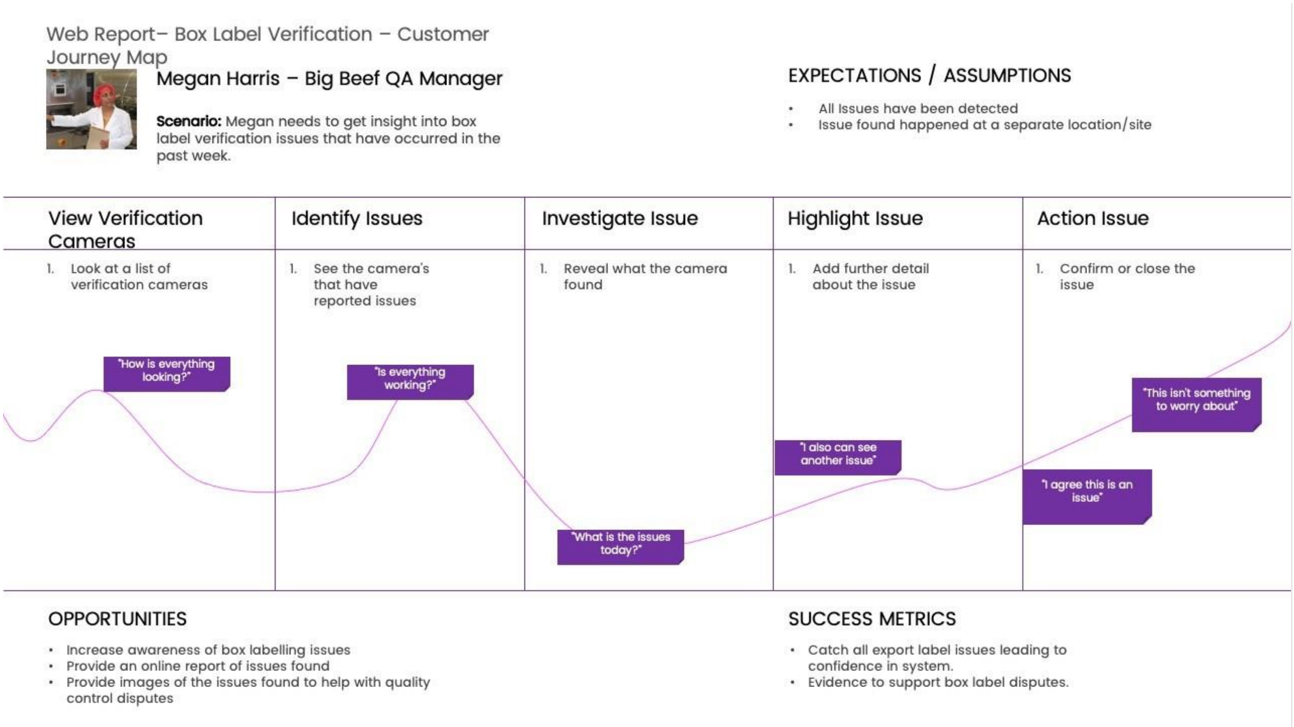
User Journey

MPC is a mid-sized Australian export meat processor with current market access to mainland China. Following a recent case of irregularities in the labelling of a small number of boxes of frozen red meat products, MPC has received a year-long ban on importation by China. Management at MPC has ordered an urgent review of the box labelling process. Currently, MPC typically produces on average 11,851 pieces of meat per week packed into 4361 boxes. The total labels used each year for both individual pieces and boxes (assuming no replacements or corrections) is 826,812.

The total cost to the company in lost revenue resulting from the ban is currently the order of AUD$0.5M but was predicted to reach $1.5M in the next financial year before the ban was put in place. Following review, management at MPC has initiated investment in a new AI machine vision-based box label verification system (BLVS). The following outlines a typical user experience for both the QA Lead and QA Manager roles.



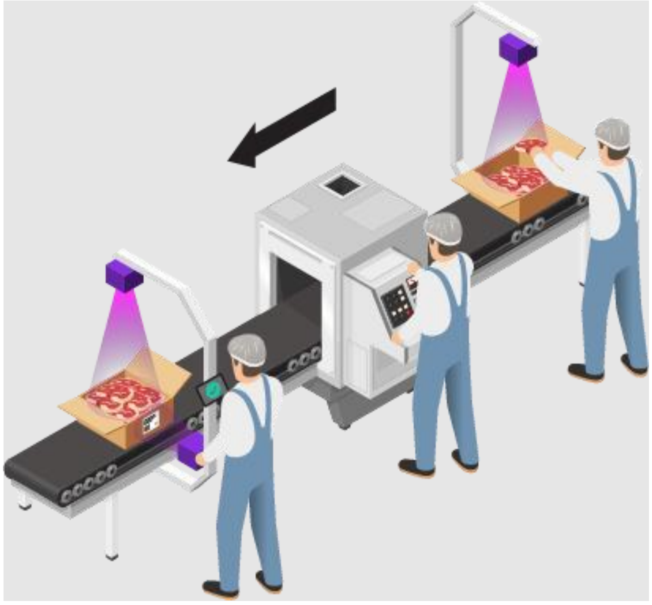
QA Lead - User Journey



QA Manager - User Journey

9.3 Appendix 3. Project Scope Summary

In addition to the consultation with the industry, equipment and testing of different equipment and holders have been conducted. It is vital that the hardware technology such as computer vision cameras is easy to set up and does not impact too heavily on the general operations. The following scope of work has been presented and discussed with each vendor.



BLV Conceptual Diagram

The purpose of this project is to develop a complementary Minimum Viable Product (MVP) version of the system to be used by meat processing organisations who are required to ensure all cartons leaving their facility have to error-free labels i.e., Labels accurately reflects what is inside the box. The system will be designed to be an easy-to-use assistive device to help organisations de-risk the chance of label errors from making their way out of a facility and into the export market.

Examples of the types of users who may come to use this mobile could be:

- QA staff (onsite): Alert staff to detect errors in real-time. Allowing them to pull cartons with label errors off the conveyor beltline.
- QA Management staff (offsite): To help investigate label errors that have been picked up by third-party inspectors e.g., China Customs, Export Customer etc.

Key Requirements

1) Camera Sensor Hardware:

i) Camera can capture a clear image of the label on the carton as it passes by

ii) Camera can capture a clear top-down shot of the contents of the carton

iii) Camera can observe human interaction with meat cuts being placed into a carton

b) Camera Sensor Hardware Integration

i) Camera sensor devices can send data to a software system to be analysed (CV, OCR, NLP, Meat ID detection).

ii) Camera Sensors can be easily installed and positioned on or near a conveyer belt system

c) Real-timeline Local View monitor to show either detected issues or scanning in progress.

2) **Website Development:** Either use existing or follow pre-scribed website design documentation and mockups for the website

a) Remote Web Page

i) Show a list of sensor devices

ii) Show a list of all cartons scanned

iii) Show a list of all issues detected

(1) Action detected issues (close, export, edit/retrain)

iv) Leverage 3rd party user management system for account login e.g., Elixar

v) Interface with 3rd party software system for data transfer e.g., sending or receiving an image or issue date

b) Real-time Local Web Page

i) Show a list of all issues detected

(1) Action detected issues (close, export, edit/retrain)

ii) Leverage 3rd party user management system for account login

iii) Interface with 3rd party software system for data transfer e.g., sending or receiving an image or issue date

3) Deep learning to observe humans placing meat cuts into a carton

a) Detect new carton interaction on a conveyer belt

i) Detect the type of meat cut being picked up and placed it into a carton (handling removal of meat cut/mistake)

ii) Determine a final itemised list of meat cuts put in the o carton

iii) Object Detect individual cuts of meat (20 categories)

iv) Send extracted data to other networked services

b) Collect enough data for a Deep Learning object detection model to detect up to 20 types of meat in cartons.

c) Cleanup and Annotate meat in carton data for model training

d) Model Training and Evaluation for 20 types of meat in cartons

4) Computer Vision (CV) to perform the label scanning

i) Detect carton on a conveyer belt

ii) Detect there is a Label

iii) Detect if the frame is clear

iv) OCR extract text

v) Form keywords from extracted OCR

vi) Send extracted data to other services

vii) Label layout doesn't affect performance

5) Deep Learning or CV to perform carton label quality check

i) Detect faded label

ii) Detect rip or damage on the label

iii) Detect part of the label is covered e.g., strapping or other foreign material

iv) Detect rotation of the label

v) Label size and position don't affect performance

6) Deep Learning (DL) to perform carton contents detection

i) Detect carton

ii) Detect there is a clear frame

iii) Object Detect individual cuts of meat (20 categories)

iv) Send extracted data to other services

b) Collect enough data for a Deep Learning object detection model to detect up to 20 types of meat in cartons.

c) Cleanup and Annotate meat in carton data for model training

d) Model Training and Evaluation for 20 types of meat in cartons

Questions about the Solution

The following list is a series of questions that have been collected when discussing outsourcing requirements of this to other vendors. We hope that the answers to these questions may be helpful in your understanding of the project.

1. Why do we need to watch people put meat into a box?

A key limitation in the current state-of-the-art carton label verification systems is we can't see below the top layer of meat in a carton or verify how many pieces were put in without human intervention. One approach to solving this issue is to watch what someone does with their hands whilst they pick up meat and place it into a carton, accounting for pieces being removed/put back in. Being able to generate an itemised list of meat cuts in a carton and feeding that into an evaluative system to determine carton label errors is key to solving one of the most problematic and common label errors. For example, it required two employees to get this data into a system

- 1 Label Print staff to count the pieces and type of meat, entering the data into a label printing machine. All performed in under 10-15 seconds per carton
- 1 QA staff to randomly verify the piece counts and type are correct. Each human who is not assisted in this process is a legitimate source of human/label error.

2. *"What type of cameras may be needed?"*

We found global shutter camera was necessary to stand a chance of capturing a clear frame of a moving object on a conveyer belt. In our experiments, we went with a Jetson AGX setup using these cameras in our prototype. So, anything that could better this we expect would work well. We used this camera for both top-down and side angles.

https://www.e-consystems.com/nvidia-cameras/jetson-agx-xavier-cameras/ar0234-gmsl2-camera.asp

The side camera (Label detection) camera did require a zoom lens. From memory was 35mm. Calculated FOV about 160x100 mm Label at a distance of 1000mm.

Objects moving on the conveyer belt move at around 1-2 m/s. Illumination was good (never an issue). Would have to track down the LUX level.

3. *"Packaging dimensions/measurements? Of the largest and smallest"*

Vacuum sealed meat cuts. ranging from

4 x (300mm x 140mm)

3 x (500mm x 100mm)

4. *"Label size/label dimensions you want to use? Of the largest and smallest"*

80mmx120mm

180mmx120mm

5. *"If part of an existing conveyor line. What is the pitch/space between each product?"*

Around 2m between each carton

6. *“Line height/current conveyor/machine height?”*

Around 800mm high

7. *“The temperature at the proposed location of the machine?”*

5-10 degrees.

8. *“How many label variations are there (please provide label dimensions)”*

Initially, we will rollout out to at least five meat processors. Each processor will have its label size and layout.

Label dimensions can range from:

80mmx120mm

180mmx120mm

9. *“How many carton shipper size variations are there and their physical dimensions”*

There are around 3-4 common carton sizes we will be looking to support.

Example dimensions of cartons are: (Width, Length, and Depth)

Type a: 350x550x150mm
Type b: 350x550x200mm
Type c: 350x550x220mm

10. *“Are all the cartons natural cardboard colour”*

Yes

11. *“Will the label be always presented for example at the bottom right corner of the carton or can it be placed anywhere.”*

Carton label placement should be clear and readable so often placed in areas that won’t be covered by strapping on the front or rear outer surface. It should also be squarely placed, however, some errors come from poor placement.

12. *“Which of the keywords do you require optical character verification for?”*

Assume all keywords on a label.

13. *“Can any of the keywords or logos be confirmed with pattern matching? Example (Australia Inspected logo)”*

Yes, we would assume that icons/symbols may require pattern matching e.g., HALAL mark. However, some symbols have registration numbers inside them that would need to be read.

14. "Cartons per minute to be inspected"

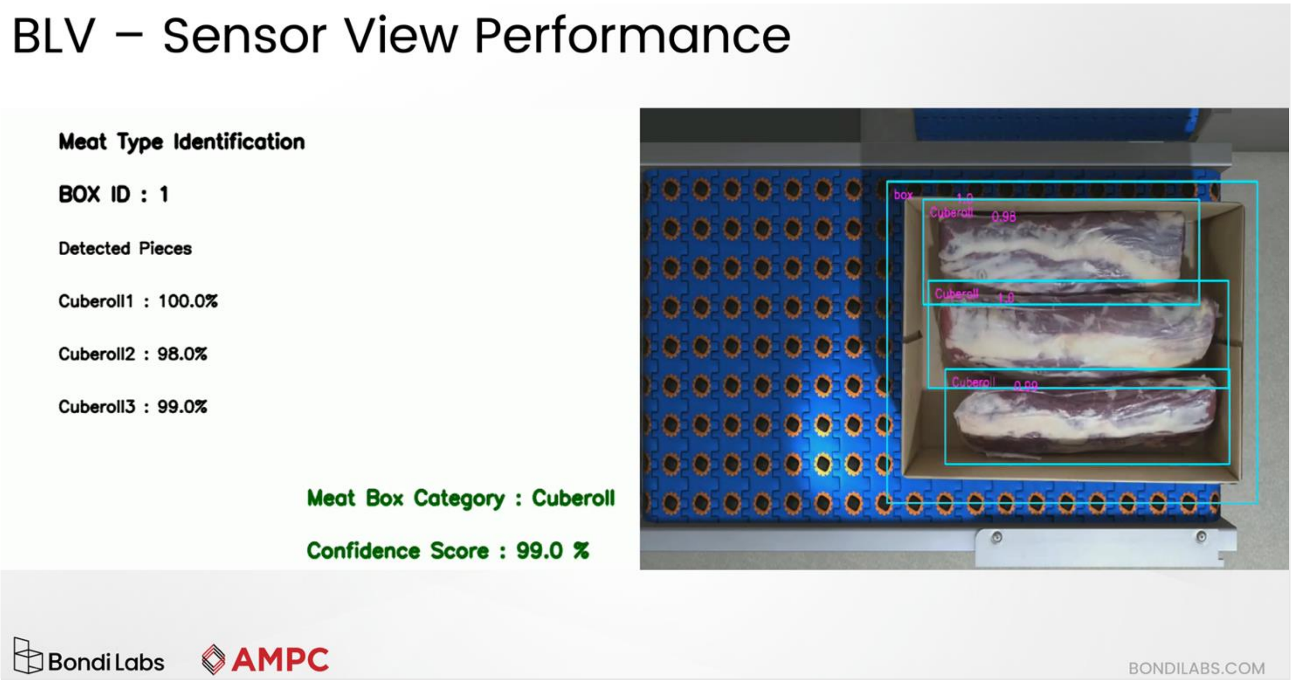
60 – 120 cartons

15. "Can we get some sample labels for all the variations in size"

Figure 2: Example Label layouts from different processors.

16. "What degree of accuracy does the meat need to be detected in the carton?"

The top-down view of meat in the box can be detected as product type/category. In our research prototype, we were able to detect 6 different cuts and count the pieces seen on top (see images below).



Prototype Meat ID Deep Learning Model object detection

Meat is in transparent vacuum-sealed bags (see video example)

For example video, the meat won't always stop, so detection may need to support moving cartons.

See the example of meat in cartons from the top camera view.

Striploin sample

Tenderloin sample

Chuckroll sample

Cuberoll sample

Rump sample

Topside_cap_off sample

Figure 3: Example of vacuum-wrapped meat in cartons

17. "What are the types of meat needing to be detected?"

Common categories are found in box 20-25 types (see attached image). Future requests may also look to expand to non-vacuum sealed cuts placed individually on a white conveyer belt, expanding to Lamb and other proteins.

Inside/Outside

- Topside
- Topside Cap Off
- Topside Roast
- Outside
- Eye Round

Round

- Round

Tenderloin

- Tenderloin
- Tenderloin Butt
- Tenderloin Center Cut Steak

Rump

- D-Rump
- Rost Biff
- Rump Roast
- Rump Cap
- Tri-Tip

Striploin

- Striploin Roast

Rib Eye

- Rib Eye Roll
- Rib Steak, Bone-In
- Rib Roast
- Whole Rib Eye

Brisket

- Brisket

Clod/Chuck

- Chuck
- Clod

Chuck Eye Roll

- Shoulder Roast

Shin

- Shin, Bone-In
- Striploin Roast

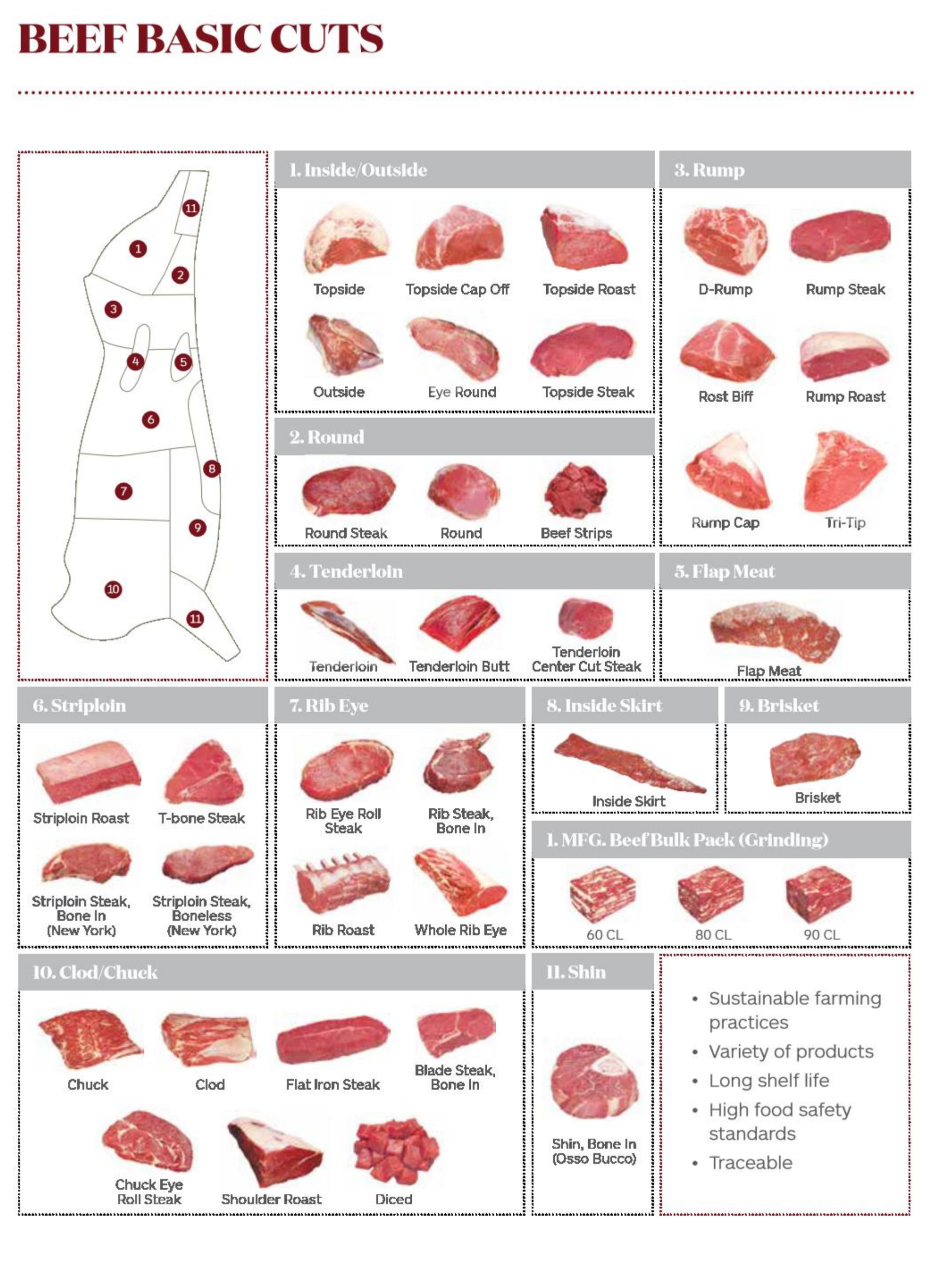


Figure 4: example of common meat cuts

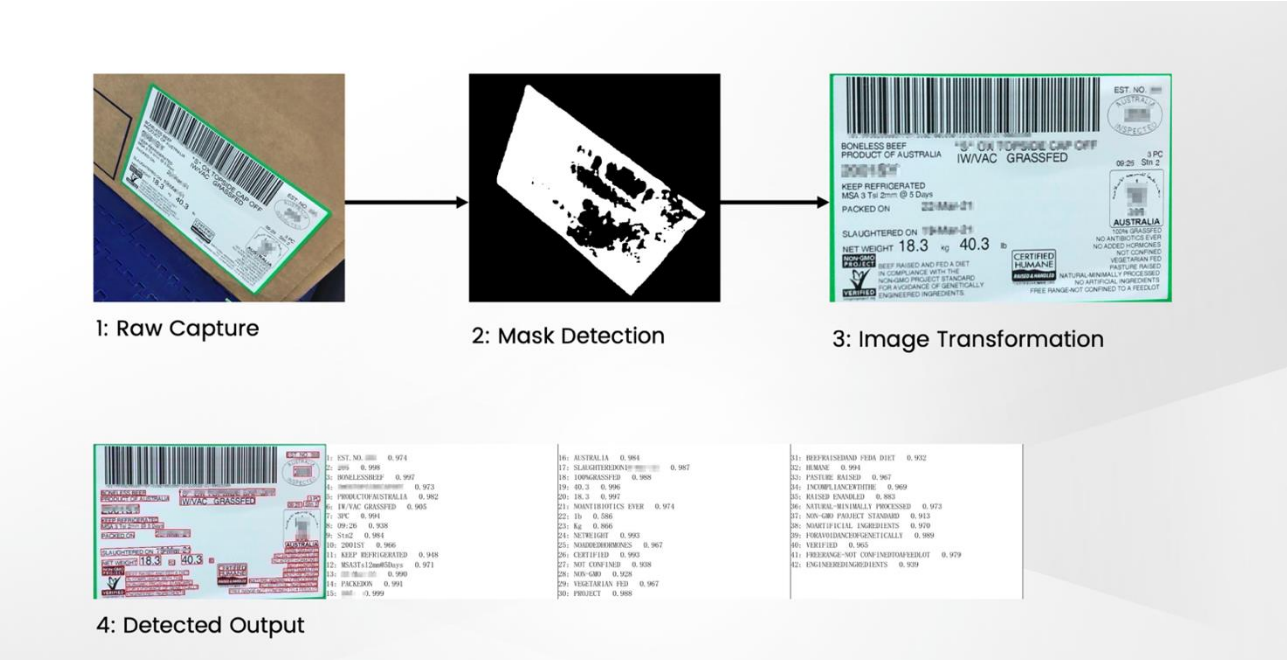
18. "What on a label needs to be detected?"

Assume everything, as it will be vital in error detection either now or in a near future. See the example label below.

2. MANDATORY LABELLING REQUIREMENTS

Illustrated is a typical labelling layout (in this instance for a carton containing primal cuts) displayed on end panels.

1. Generic Identification (Includes the species and a Bone-in or Boneless statement)
2. Country of Origin
3. Category Description
4. Product Identification
5. Packaging Type
6. Packed On and Best Before Dates (If required by the importing country)
7. Net Weight Statement
8. Company Name and Address
9. Refrigeration Statement
10. Australia Inspected Stamp (AI)
11. Establishment Number
12. Customer Country Markings


1: Raw Capture
2: Mask Detection
3: Image Transformation
4: Detected Output

9.4 Appendix 4 – Industry Comments

RQ1: How many potential labelling errors can an automated system detect reliably and validly?

ORG1: *"I know internally it is a concern- while I do not have direct access to all of the data relative to this problem, it is my understanding that we receive a number of complaints around things like contaminants (hair, metal) but the majority of complaints from clients seem to relate more to the BL problem- wrong cuts, incorrect count- even wrong brands going out from plant."*

ORG2:

"Errors in labelling

- Image faded – cannot be read by a scanner

- Incorrect product described

- Inserts missing

- Label/inserts mismatch

- AI stamp or required text may not print onto label

- Inability to confirm translations on carton – Day to day check"

ORG3: *"With the present process we capture dozens a day- but this is not automated and it is dependent on humans, removing the dependency on the human element here would be a huge plus. We currently utilise the use scales operators for label verification. Another point here that should have great benefit is the language side of the label. We need to employ people who speak different languages to read and understand multiple labels going to many different countries. Of course, we select Chinese readers for C Chinese labels etc however some countries request bilingual labels, French, Chinese, German, Arabic, and Swiss- cause issues with employment all the time- we have difficulty enough getting good team members without having to find ones that are proficient readers of other languages. Regional dialect- overlap is usually enough with different dialects of the same or similar languages but can cause a potential problem if a specific importer asks for a specific dialect. Machine learning here again would be a huge plus."*

RQ2: Can meat cuts placed into a carton be detected as it occurs using computer vision?

ORG2: *"I think some companies would welcome it. We put outs into bags which will distort the image of the cut sometimes. However, I would be interested in seeing if we can."*

ORG3: *"Theoretically possible- however on our site the camera placement could be a concern given space in these stations currently- very closed in section and it would be almost impossible (based on current human intervention) to get more equipment in here without being problematic. Might have to be some investigation- platform and carousel currently, three levels of belts, lots of hands and heads."*

RQ3: How can automated label verification systems be adopted broadly by any meat processors, even by those who have small-scale operations or limited connectivity?

ORG1: *“My concern is that I do not think we even understand how big a problem this is for us.”*

ORG1: *“We have two places where the boxes are checked- these are very dependent on skills, experience and speed of the supply line on the day. It is not always possible to have your most skilled people on these stations- staff retention, illness, leave or cannot get good team members.”*

ORG1: *“As I mentioned- I don’t think we know or understand how big the concern is. The data does not come directly to my role so there may be more information here than I am aware of however there are a lot of issues here. How many clients receive better quality cuts or brands and don’t say anything? We have problems with label reading, piece identification, brand recognition in the carton and piece count. If we could just identify and fix a few of these we would be better off.”*

ORG2: *“Not sure across the industry – my drivers are market access, we lost China for labelling errors (5 cartons with labelling missing or mismatched). Humans get tired and looking at over 14K of cartons a day is a big ask. If we are being realistic those staff might look at 1% of those labels with the detail required. The only true solution available to us is label verification and RFID identification.”*

ORG3: *“Once we have proven a system it should be quite simple to provide an industry-wide standard- all following the same standards currently as we are all doing the same thing here- meaning the bulk of what we do will be the same across the industry- same cuts, similar product, coding built into Ausmeat qualifications as an example. Everyone could adopt a solution that was industry-proven and the outcome measures or savings could be demonstrated and proven.”*

RQ4: Can meat processing staff become confident and ready to utilise an automated label defect detection system?

ORG2: *“I think everyone has resistance at first to automated systems until they realise it’s a tool to help them with their role in the business. Additionally, I think it comes to staff selection and training.”*

ORG3: *“As an industry, we are very result-oriented, if we can prove a successful tipping point- the industry will get on board, Training is of course important (specific and useful) for team members as we are creatures of habit. We are open to new processes, but it does take a long time to train the team and as an RTO we always find that face to face face-to-face is the strongest way to train our teams and usually achieves the highest level of success.”*

RQ5: Quantification of production statistics such as boxes packed/day, types of meat cuts boxed, staffing levels

ORG2: “*The statistics I would like to see*

- Overall label compliance/per labelling station

- Details error list/operator/chain/product/who

- Pixel or image clarity report per printing station

This could be done per operator.”

ORG3: *"As soon as you are capturing vision or video you create a new auditable source of truth, this could potentially be used by multiple sources or auditors for multiple functions or audits."*

RQ6: What are the operational outcomes resulting from error identification? i.e. what would you do with a box flagged as having a label error?

ORG2: *"I would have a tagging system that either kicks the carton off the main conveyor belt to a relabelling station where the details of the fault could be reviewed and a label reapplied and sent back through the vision system or a visual assessment depending on the setup and company's circumstances."*

ORG2: *"I firmly believe that a vision system combined with an RFID set-up will address 99.9% of our labelling errors."*