Final Report

AMPC
AUSTRALIAN MEAT PROCESSOR CORPORATION

Automated AI

Automated AI / X-Ray Enabled Primal/Box/Label Evaluation

Project Code
2024-1083

Prepared by
Miki Keep

Published by
AMPC

Date Submitted
16/06/2025

Date Published
16/06/2025

Contents

1.0 Executive Summary

This collaborative R&D project with Foss and SIA aims to improve carton and label verification in Australian processing facilities through the development of an AI-enabled Dual Energy X-Ray imaging system. This initiative involves upgrading existing technology (Meat Master) systems, integrating essential hardware, and implementing an AI overlay for enhanced adaptability.

This projects comprehensive approach includes the integration of the system into existing controls, enabling repeatable rejection processes. Subsequent phases involve running cartons through production rates to obtain baseline X-ray images and ensure accurate labelling. The complied image library will serve as the foundation for rigorous model testing.

During model testing, key verification processes will be executed:

1. Correct product verification will leverage X-ray images of known products, employing AI technology to access each carton's adherence to product descriptions. The rejection of at-risk cartons at the chute will allow operators to verify correctness or initiate re-work. Random manual selections and monitoring complaint trends will validate the system's accuracy and potential reduction in mislabelled products.
2. Chemical lean verification will involve random testing of trim cartons to validate measured CL, adjusting parameters based on Foss Food Scan results.
3. Foreign object detection will be meticulously monitored, recording results to establish system reliability.

Ultimately, project success will be determined by testing results against customer requirements and predefined acceptable levels outlined in the proposal. This undertaking signifies a transformative step in the research and development toward industry-wide adoption of advanced carton and label verification systems.

2.0 Introduction

The purpose of the Automated AI / X-Ray Enabled Primal/Box/Label Evaluation project was to create a secondary verification process to confirm that carton label claim matches the carton contents with a target of >97% product identification across the trained models. This was done by creating an AI algorithm with screened data sets. Though this process an image and meta data prediction was created to use for assessment on the eligible cartons. This is done by evaluating the x-ray image and meta data against the carton label claim. If the carton is outside of the trained AI algorithm specifications then the carton will be rejected. If the AI algorithm assessment meets another one of the trained AI models it will put forward a 'detected product'.

3.0 Project Objectives

- Address challenges/limitations from previous project using X-ray technology combined with AI machine learning computer program.
- Finalise a commercial solution and verify performance.
- To train 10 product algorithms to identify product type initially >96% of cartons with a certainty threshold of >50%, a certainty distance of >30% across 100% of the products. This target has been refined to limit false detections close to 0. At Milestone 6, the target will be shifted to >97% product identification.

4.0 Methodology

The project aims to transform carton and label verification processes by leveraging an AI-enabled Dual Energy X-Ray imaging system. This initiative, seeks to enhance accuracy and efficiency through the following process:

1. On-Site Assessment and Stock Keeping Unit (SKU) Identification:
    a. Nolans to engage Foss and SIA representatives to assess historical data and ensure equipment specifications align with site requirements.
    b. Identify the top 10 high-risk SKUs crucial for the project's foundation.
2. Preliminary Data Collection:
    a. SIA reviews collected data, identifies errors, and collaborate on accuracy assessment.
    b. Conduct an initial simulation for early feedback, refining project objectives.
3. On-Site Equipment Upgrade and Live Production Setup:
    a. Upgrade on-site equipment in collaboration with Foss and SIA for efficient data capture and rejection.
    b. Set up 4 SKUs in a live production environment, ensuring accuracy at production speed.
4. Data Verification and AI Model Tuning:
    a. Dedicate substantial time to verify generated data accuracy.
    b. Adjust the AI model based on captured information and ongoing process feedback.
5. Scaling Up:
    a. If successful, integrate an additional 6 SKUs into the system.
    b. Target over 5,000 images for each product type to ensure comprehensive testing.
6. Training:
    a. Nolan’s manages grouping and labelling, allocating four weeks per 10 classes.
    b. Initiate neural network training by conditioning it with categorized X-ray images.
7. Validation:
    a. Validate neural network results using an additional set of 500 categorized images.
    b. Target specific defects such as;
        i. Primal type and product code mismatches e.g., wrong product
        ii. Chemical lean outside tolerance
        iii. No outer label/ correct labelling
        iv. Foreign object detection
8. Overall Project Evaluation:
    a. Evaluate project success against predefined customer requirements and acceptable levels outlined in the proposal.

5.0 Project Outcomes

This project has delivered a working AI-enabled Dual Energy X-Ray imaging system which has successfully found cartons with a mismatch of product to label identification, reducing the risk of cartons being sent out with a mismatch of product to label claim. When analysing the true rejected cartons, it was observed that there were common cuts that were mislabelled as another cut. With this the total value of loss through down grading or giving away product can be seen to average $222,160.71.00 per year. With the AI algorithm detecting these products it has resulted in an average $222,160.71 saving per year. This equates to a 13-month payback period. The intangible customer relations are also benefited from the AI algorithm as this has mitigated the likelihood of sending product with a mismatch of product to label claim. This keeps the customer satisfied as they are receiving what they ordered and also reduces the customer complaints and non-conformances for out of spec product. The use of a historical database allows for the lookup of a carton label including x-ray image and meta data as the first point of verification if a claim is sent through. This record shows all x-ray results, AI outcome and rejection statuses for that carton. The customer satisfaction is greatly important throughout industry and by delivering correct product that was purchased along with it being delivered within specifications will see a continued growth with customers.

The AI algorithm has a 99% correct product identification. This is the percentage of cartons that were eligible for assessment matching the carton label and the true rejects identified. There is overall 1% of false product identification seen through the false rejects from the assessed cartons. This evidently has met the project objectives of >97% product identification for the 10 SKU's.

5.1 On-Site Assessment and Stock Keeping Unit (SKU) Identification:

The following 10 SKU's where selected for the project; Undercut Knuckle, Striploin, Rostbiff, Oyster Blade, Neck Bones, Leg Bones, Inside Cap Off, Cube Roll, Bolar Blade and Brisket Point End. These products have been selected either as they are hard to identify through x-ray image data, commonly mislabelled and covers most of the prediction models used on the Foss X-ray. These 10 products have been broken into two groups for this project; first 4 - Cube Roll, Neck Bones, Rostbiff and Striploin and final 6 - Undercut Knuckle, Oyster Blade, Leg Bones, Inside Cap Off, Bolar Blade and Brisket Point End.

Nolan extracted 6000 images for each of the 10 products. These were then screened by Nolan before being sent to SIA to remove any that were blurry, jammed or incorrect product. This provided SIA with a clean data set that can be used for initial training of the model. Table 1 below shows screen images. The Bad Images are made up of blurry images, jammed cartons and incorrect product.

Products	Good Images		Total Bad Images	
	Number	Percent	Number	Percent
Undercut Knuckle	5938	98.97%	63	1.05%
Striploin	5995	99.92%	6	0.10%
Rostbiff	5937	98.95%	64	1.07%
Oyster Blade	5950	99.17%	51	0.85%
Neck Bones	5757	95.95%	244	4.07%
Leg Bones	5678	94.63%	323	5.38%
Inside Cap Off	5994	99.90%	7	0.12%
Cube Roll	5881	98.02%	119	1.98%
Bolar Blade	5879	97.98%	122	2.03%
Brisket Point End	5728	95.47%	273	4.55%

Table 1: Screen Data Set

5.2 Preliminary Data Collection, Training and Validation:

SIA created an 'Operator Game' that was able to be used by competent operators to provide an understanding of the human ability to identify products based on X-Ray image only. The data collected through this exercise was analysed by SIA finding an overall 83% correct product identification. This tool would be great for training purposes to enhance the operator's abilities to identify cuts against an x-ray image.

SIA initially used 2000 data sets for each of the first 4 SKU's and put these through both image base prediction and meta data-based prediction. 500 samples were then put through this prediction with an overall ≥86% identification for image prediction and ≥85% identification for meta data prediction. This can be seen in Appendix 9.4.

5.3 On-Site Equipment Upgrade and Live Production Setup:

Installation of software and hardware including W10 upgrade, rejection terminal, reject signal, SIA AI algorithms, setup of SQL table, PLC changes and prediction models. Once the installation was completed the system was checked for functionality. This was done by using a pallet of different types of products that would cover all prediction models and the first 4 implemented AI models. Through testing it was confirmed that the X-ray, AI algorithm and rejection was working. The AI algorithm rejection was left disabled although it was still collecting the data that would be assessed before enabling the AI algorithm rejection. This was done to ensure that there would not be a significant amount of rejects caused by this model especially false rejects. Figure 1 below shows the AI rejection terminal. This terminal has aided operators to fix rejected cartons quickly as it provides an image, carton label claim, x-ray meta data and the rejection reason.

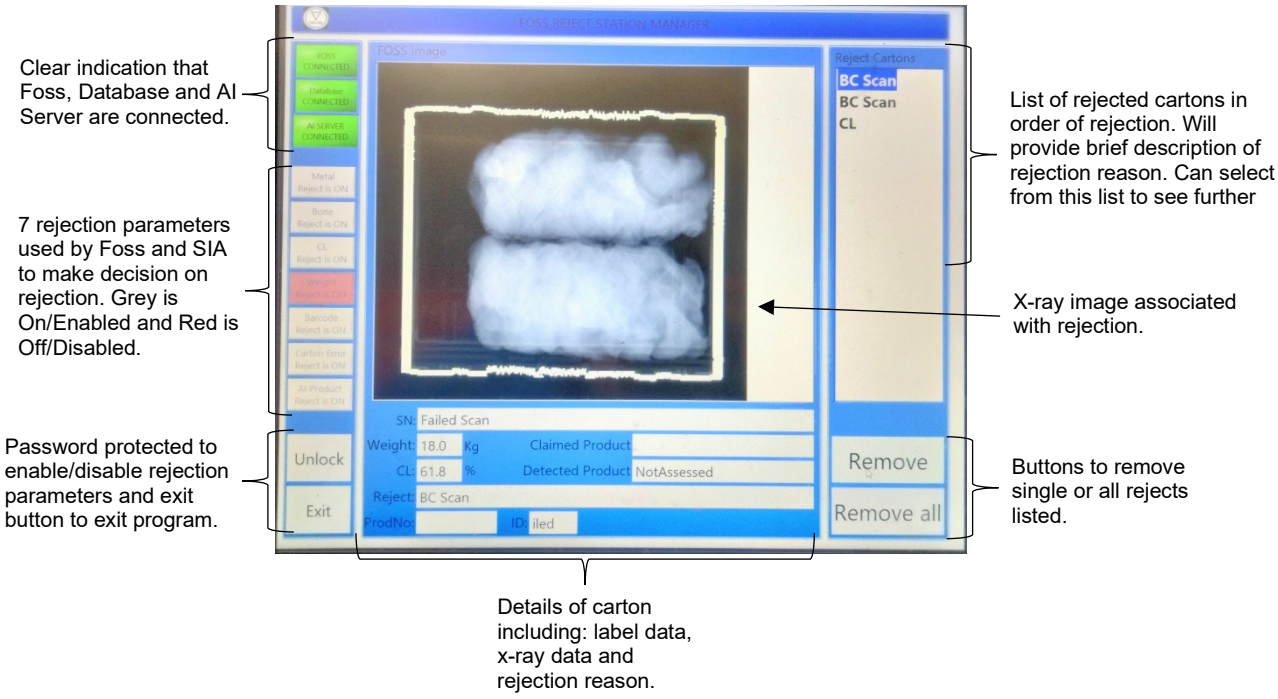

Figure 1: Rejection Terminal

5.4 Data Verification and AI Model Tuning:

83 working days of data was able to be collected and analysed with a total of 99,855 cartons eligible for assessment by the AI algorithm. Only 97,109 cartons were evaluated with 1,505 of these being flagged as AI rejects. The AI model needed to answer two questions to decide if the carton claim is correct or not. If these cannot be answered it will not be assessed. a) 'Am I confident that the inspected is NOT what is claimed via the barcode label? and b) 'Am I confident that the inspected is another product I know?' SIA analysed this data and found the average recognition confidence ranged from 65%-100% dependant on the product as seen in table 2 below. From these findings it was recommended to add an operator feedback tool to the rejection terminal, AI algorithm rejection default to on and work around the AI algorithm to mitigate the 'unable to assess' cartons which equated to 2,746 of AI eligible cartons.

Product	Number rejects	Avg. recognition confidence
Bolar Blade	185 (0.19 % of AI inspected)	91 % (9518 cartons)
Brisket Point End	103 (0.10 % of AI inspected)	96 % (17923 cartons)
Cube Roll IV	525 (0.54 % of AI inspected)	80 % (13848 cartons)
Inside Cap Off	66 (0.07 % of AI inspected)	92 % (16888 cartons)
Leg Bones	3 (0.003 % of AI inspected)	99 % (4182 cartons)
Neck Bones	5 (0.005 % of AI inspected)	100 % (4182 cartons)
Oyster Blade IV	63 (0.06 % of AI inspected)	87 % (2642 cartons)
Rostbiff MV	156 (0.16 % of AI inspected)	66 % (1744 cartons)
Striploin	240 (0.25 % of AI inspected)	81 % (9049 cartons)
Undercut Knuckle MV	159 (0.16 % of AI inspected)	65 % (2505 cartons)

Table 2: Initial Integration Data

5.5 Scaling Up:

SIA implemented an updated AI algorithm with one of the main changes being the removal of question b) 'Am I confident that the inspected is another product I know?' leaving just question a) 'Am I confident that the inspected is NOT what is claimed via the barcode label?' to be answered. This change made every eligible carton to be assessed by the AI algorithm. When the AI algorithm could not detect what the product 'should be' it will still be an assessed and not put forward a 'detected product'. All 10 SKU's were using the AI algorithm and being evaluated which did not see an increase in rejections from the X-ray indicating that the AI algorithm is working and not causing unnecessary rejections for operators to handle.

5.6 Overall Project Evaluation:

14 working days of data were collected from when the update was implemented presenting 17,296 cartons eligible for assessment by the AI algorithm. 100% of these cartons were assessed with the updated algorithm. All but 1 of the 10 SKU's have a ≥70% median recognition confidence as seen in Table 3 below. A total of 442 cartons were rejected and evaluated by a competent operator to determine if the rejection was true. This found 46 of these cartons were true rejects with a mismatch between label claim and carton contents, 218 cartons where false rejects and 178 cartons rejected with undesirable presentation. The cartons rejected with undesirable presentation is a result from training the AI models with clean screened data sets that were presented as per compony specifications.
Evidently the Automated AI / X-Ray Enabled Primal/Box/Label Evaluation project has met the objective to refine false detections close to 0 and identify product type to >97% product identification.

Product	Number Rejects	Avg. / Median Recognition Confidence
Bolar Blade	63 (0.36 % of AI inspected)	85 % / 96% (1150 cartons)
Brisket Point End	92 (0.53 % of AI inspected)	91 % / 100 % (2926 cartons)
Cube Roll IV	139 (0.8 % of AI inspected)	67 % / 80 % (2420 cartons)
Inside Cap Off	17 (0.098 % of AI inspected)	89 % / 96% (3334 cartons)
Leg Bones	0 (0 % of AI inspected)	100 % / 100 % (552 cartons)
Neck Bones	1 (0.006 % of AI inspected)	100 % / 100 % (2986 cartons)
Oyster Blade IV	28 (0.16 % of AI inspected)	78 % / 89% (504 cartons)
Rostbiff MV	0 (0 % of AI inspected)	46 % / 45 % (222 cartons)
Striploin	65 (0.38 % of AI inspected)	68 % / 83% (1772 cartons)
Undercut Knuckle MV	37 (0.21 % of AI inspected)	65 % / 70% (984 cartons)

Table 3: Update Integration Data

6.0 Discussion

Training of an AI algorithm to compony product groups has observed great success in identifying mislabelled product. The AI algorithm will reject a carton when the specifications for that carton are not met. Once the carton is rejected the data and rejection reason is displayed on the rejection terminal for easy identification of what is wrong leading to ease of rectifying the problem. The project has presented 98.8% true product identification and correctly picked up mislabelled cartons that were able to be rectified.

- 100% of AI identified cartons are being assessed using Meta and Image data.
- AI algorithm presented with 98.8% true product identification. True product identification is the correct cartons plus the true rejects that the AI algorithm detected.
- All cartons rejected by the AI algorithm were further assessed by competent personal to confirm what the product was. This confirmed that 0.27% of the rejected were rejected with a mismatch of label to product (true rejects) and 1% of product was rejected with undesirable presentation. This was a result of training the AI algorithm with clean and correct data sets.

7.0 Conclusions / Recommendations

Overall, the AI algorithm is working and has successfully flagged cartons with a mismatch of product to label identification, reducing the risk of cartons being sent out to customers with a mismatch of product to label claim. The AI algorithm has a 98.8% correct product identification. This is the percentage of cartons that were AI assessed matching the carton label and the true rejects identified. There is overall 1.2% of false product identification seen through the false rejects from the AI assessed cartons. This evidently has met the project objectives of >97% product identification for the 10 SKU's.

Foss will have a stand at the upcoming 2025 AMPC Showcase. Foss and SIA will present a technology package showcasing the AI-Enabled Dual Energy X-Ray imaging system. This will provide opportunity for Meat Processors to explore the technology.

Evaluation of the 46 true rejected cartons has provided a breakdown of what the label claim was against the carton contents. Further analysis was done using reported market pricing (Des Moines, 2025) as a baseline to find the product value lost between the carton label claim and carton contents. This has been broken down into two sections; customer complaint which includes product that would have been supplied at less value, downgraded product and customer upgraded product that would have been supplied with greater value. The value has been broken down into these two categories as from past experience you typically do not hear about the product that is 'upgraded' where as if supplied product is a 'down grade' a customer complaint, non-conformance, investigation, rectification is required. An administrative cost has been allowed for in the CBA which considers the time for complaint management, investigate, rectification, re-worked cartons, market access maintenance and auditing costs.

Table 4 below, shows the potential cost over 14 working days and what this equates to per annum. The implementation of an AI enabled box recognition system is $60,000.00 + GST including the hardware, software, reviewing and monitoring of the system. The current installation has shown that a cost saving of $255,070.86 per annum is achievable with the detection of mislabelled cartons. The return on investment is 2.82 months. The intangible customer relations are also benefited from the AI algorithm as this has mitigated the likelihood of sending out product with a mismatch of product to label claim. This keeps the customer satisfied as they are receiving what they ordered and also reduces the customer complaints and non-conformances for out of spec product. Carton claim is important in the red meat industry and by delivering correct product that was purchased along with it being delivered within specifications will see a continued growth with customers, keep the customer satisfied, gain further market access and enhance brand integrity.

	Customer Complaints	Customer Upgrade	Administrative	Total
14 working days (46 cartons)	$3,573.31	$2,497.27	$7,664.00	$13,734.58
Per Year	$66,361.53	$46,377.90	$142,331.43	$255,070.86
Hardware/Software Install (10 Products)				$60,000.00
ROI (Months)				2.82

Table 4: Cost Benefit Analysis

Recommendations:

1. Re-training of the 10 implemented SKU's could increase the certainty of the AI algorithm prediction and further reduce the amount of false rejections.
2. Setting up additional classes to incorporate all products will again elevate the AI algorithm. Question b) 'Am I confident that the inspected is another product I know?' could also possibly be re-introduced again alongside question a) 'Am I confident that the inspected is NOT what is claimed via the barcode label?'. This would enable the AI algorithm to put forward an alternate to the carton label if it does not match. With only 10 SKUs being setup, many cartons come up with 'unknown product' due to only having 10 classes that it can reference.
3. To further improve the evaluation process, it would be feasible to investigate if the AI algorithm can be further refined by implementing a continues training tool. This would tune the AI model and become more accurate with every carton assessed. Using the operator feedback tool 100% of the time would also improve the model or offer further training material if the AI algorithm was continuously using new data to improve the models.
4. Merging of the Meta and Image data.
5. Utilising the AI algorithm to detect cartons that are packed outside of compony specifications – undesirable presentation. This could be seen by implementing an additional button on the rejection terminal beside the product confirmation button for undesirable packaging. When certain cuts are packaged outside of company specifications it can present through the x-ray as different product that has similar characteristics. By

continuing to reject these cartons the operator has the opportunity to amend the presentation of the carton before it is sent to the customer.

8.0 Bibliography

Des Moines, I. (2025, June 23). *National Daily Boxed Beef Cutout And Boxed Beef Cuts - Negotiated Sales - Afternoon.* Retrieved from United States Department of Agriculture: https://mymarketnews.ams.usda.gov/viewReport/2453

9.0 Appendices

9.1 SIA_Nolan Final Summery

9.2 X-Ray & Rejection Operation

9.3 SIA_Production Integration Report 2

9.4 SIA_AI Test Report 1

9.5 SIA_Production Integration Report 1

9.6 USDA National Daily Boxed Beef Cutout and Boxed Beef Cut Pricing