Naked Primal Cut Recognition Vision System Trial in Plant

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1.0 EXECUTIVE SUMMARY

Red meat processors currently utilise manual skilled labour for their naked primal cut identification and bagging procedure. This requires significant labour from staff trained in the identification of primal cuts. The misidentification of primal cuts from operator error is also a problem faced by processors. These issues come at significant cost to red meat processors.

To overcome these issues and reduce production costs, a Naked Primal Cut Recognition software package was developed in a previous AMPC project (2017-1064, Development of Naked Primal Cut Recognition Software), and this project now integrates that system into a red meat processing facility for a live trial. This solution utilises a 3D stereoscopic line scan camera placed over a primal cut transfer conveyor to capture a high-resolution 3D image of each primal cut as it passes underneath. A neural network was developed to process the acquired 3D image to determine useful feature data and identify the type of primal cut.

After finding a suitable red meat processing plant to host the project (Oakey Beef Exports), the existing vision system was modified to comply with the hygiene and cleaning standards of the plant and to suit the dimensions and space constraints of the conveyor and surrounding area. This was achieved by manufacturing a compact stainless steel frame and enclosures for the sensitive components such as the stereoscopic camera, lights and computer. The system was subsequently transported to and installed on site.

A neural network was trained to identify 7 different primal cuts as outlined in the project scope. 1169 images of primal cuts were gathered on site by the vision system, and subsequent analysis of these images yielded the data which was used to train the neural network. The newly trained neural network was deployed into the Naked Primal Cut Recognition software package and the live trial was run.

After analysing the results of the trial it was found that the recognition software was able to correctly identify the primal cuts with an accuracy of 90%. This is an impressive result for the first live trial of a system developed in a workshop environment, and we believe that further developments could be made to increase the accuracy of the system.

2.0 INTRODUCTION

Meat processing facilities incur significant labour costs associated with the identification, manual bagging and labelling of primal cuts and trims. Primal cut bagging and labelling is currently a labour intensive and completely manual step in the meat packing process where the cuts can easily be misidentified. This step requires operators to identify and label cuts of meat prior to packing, storage and dispatch. The introduction of automated solutions to perform this task will significantly reduce labour required as well as potentially allow for 'real time' performance feedback of boning and slicing operations, presenting significant economic savings.

The intent of this project is to take the technology developed during AMPC Project no: 2017-1064 "Development of Naked Primal Cut Recognition Software" and implement the system in a meat processing plant for a live trial. The system made use of 3D imaging sensors which captured and processed the 3D scene and profile of the primal cuts in real time. Information such as dimensions, fat content and shape are calculated from the 3D data and used to identify the naked primal cut.

3.0 PROJECT OBJECTIVES

- Determine if the Naked Primal Cut Recognition Software as developed and tested in the workshop environment during AMPC Project 2017-1064 can be successfully installed and integrated into a meat processing plant.
- Determine if the Naked Primal Cut Recognition Software can successfully identify and measure its designated subset of 5 to 7 primal cuts and differentiate them from a full range of production cuts passing under the camera.
- Trial system in plant and report on its efficacy and suitability to the plant's operations.

4.0 METHODOLOGY

4.1 Identification of a Suitable Plant

A suitable meat processing plant and subsequent location in the plant was to be identified to accommodate the vision system. An Expression of Interest to host the project was circulated to AMPC members, and after responses were finalised, site visits were conducted to evaluate each plant with considerations to space requirements, product range, conveyor specifications, ability to obtain primal cut weight, and ability to obtain additional data such as the primal cut type. The chosen plant was Oakey Beef Exports at line three for the following reasons:

- There was ample free space surrounding the line.
- A full range of primal cuts would travel down the line. From this, a relevant subset could be selected for identification.
- Each primal cut was identifiable and tracked from the moment it is cut.
- Upstream of the vision system, there was an in-line check weigh which could provide weight measurements of the primal cut.
- The primal cuts were spaced approximately 1 metre apart and were centred on the conveyor belt.
- Timestamped data relating to each primal cut (containing information such as weight and type) passing under the vision system could be obtained. This could be cross-correlated for further training of the system. During testing, the prediction (type) of the primal cut from the vision system could be compared to the true type of primal cut.
- There was a suitable location to mount a rotary position encoder onto the conveyor.

4.2 Customisation & Installation of System

The vision system initially developed in AMPC Project 2017-1064 was run as an in-house trial, and as such modifications were required for integration on site as well as to meet the standards of Oakey Beef Exports' boning room. The following system requirements were identified:

- All equipment needed to be designed taking into account the site's sanitary guidelines. All equipment needed to be food grade with an IP67 rating and be capable of being washed down at the end of each day.
- The system needed to be designed in a way to minimise disruption to the plant. This would mean:
    - A compact design with a small footprint would be ideal so the system would not get in the way of plant staff.
    - Nothing would be bolted, drilled or otherwise alter the existing equipment at the plant.
- Selection of equipment should be appropriate to the conveyor's speed, colour and width, the position and height of the primal cuts, and surrounding environment.

Most of the components from the previous project were modified to satisfy these requirements. The following points detail the modifications:

- Since the conveyor at Oakey Beef Exports was very similar in colour and width to the conveyor used for the in-house trial, it was suitable to use the same camera and lights for the live trial. A stainless steel housing and frame was manufactured to enclose these components so that it would meet the IP67 rating. Thin high optical efficiency float glass was used as windows for the cameras to allow light to pass through with minimal distortion to not affect the 3D processing. Initially the windows were made of optical grade polycarbonate, but it became apparent that the sodium hydroxide used in the cleaning chemicals reacted with the optical film on the polycarbonate, causing degradation in the image quality. It was also found that hard water used on site would cause mineral deposits to accumulate on the glass causing further degradation in image quality. A cleaning procedure using phosphoric acid was developed to counter this, and a waterproof bag to enclose the camera housing was acquired to protect the float glass during daily cleaning. The frame was designed as a free-standing structure with two main bodies (upper and lower half) to allow it to be easily separated, transported and assembled with minimal disturbance to Oakey Beef Export's equipment. Anti-vibration machine feet were selected to allow for height adjustment and levelling of the frame on site.

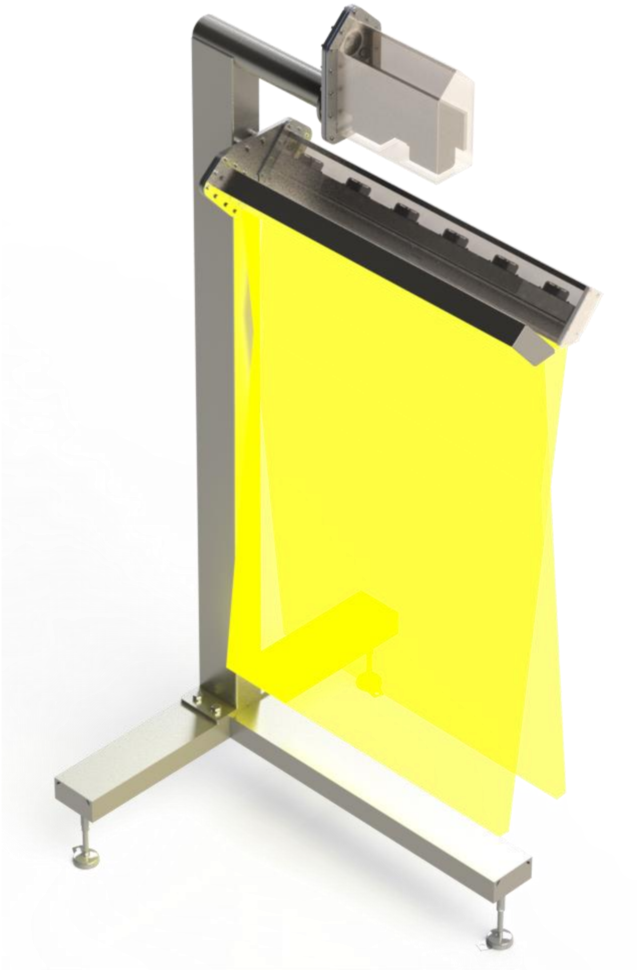


Figure 1: Rendering of frame and enclosures

- The rotary position encoder used in the in-house trial was an IP67 rated, programmable, incremental encoder; thus satisfying the requirements. To enable attachment to the 30mm conveyor shaft, an adapter was designed which would attach to the conveyor shaft through grub screws. This meant that no modifications to existing hardware would be required. A double loop coupling with stainless steel hubs and a food grade polymer connecting element was also selected to account for shaft misalignment.

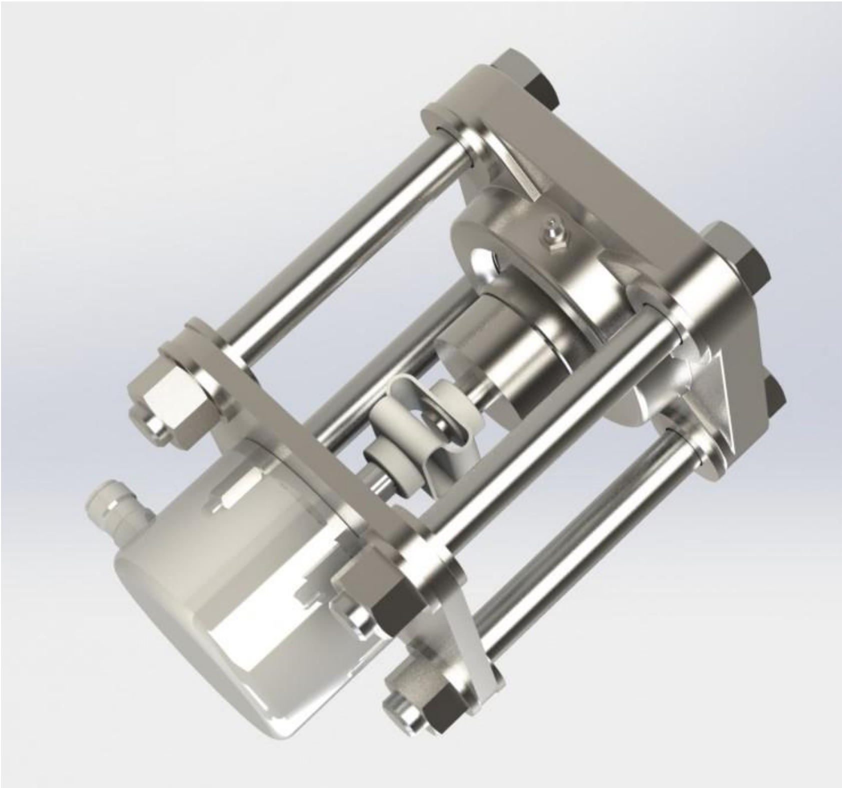


Figure 2: Rendering of rotary position enclosure and adapter

- The photoelectric sensor used in the in-house trial did not satisfy the wash down requirements and was not a suitable component to have an enclosure, so the acquisition of a new photoelectric sensor was necessary. The selected sensor was a laser diffuse photoelectric sensor with background suppression. Being a laser diffuse sensor meant that a reflector was not required, enabling simpler installation. The incorporation of background suppression also made it ideal for sensing of a darker product with a lighter or reflective background.

- A stainless steel electrical cabinet was assembled to house the vision processing computer, LED light drivers and other electrical components. A panel mount industrial monitor was also mounted to the face of this cabinet to display the output of the vision processing computer.

Figure 3 and Figure 4 shows the designated area before and after installation, while Figure 5 and Figure 6 shows alternate views of the installation.

A list of the all the major hardware components can be found in Appendix 8.1 Major Hardware Components. Details of the computer parts can be found in Appendix 8.2 Vision Computer Components.

Figure 3: Area before installation

Figure 4: Area after installation

Figure 5: Side view of vision system


Figure 6: Back view of vision system

4.3 Developing the Neural Network

Developing a neural network involved several steps. In order to teach the neural network to identify different primal cuts, training images needed to be acquired along with the name of the primal. Ideally there would only be one primal cut per image. For each primal cut imaged, several parameters are calculated based on salient features; the collection of these parameters form a feature vector. Ideally, the resulting feature vectors would be similar within the same primal cut, but would vary between different primal cuts. The neural network would then be trained on the feature vectors and cut types.

4.3.1 Data Collection

A removable 10TB hard drive was used to store the acquired images for subsequent processing. The system saved a set of four images for each primal cut that passed beneath the cameras: the raw master and slave images from the dual cameras, as well as the rectified and disparity height map generated from the 3D processing. After collecting data for several days, the hard drive was removed and delivered to Strategic Engineering's office for offline processing.

Several challenges were encountered when attempting to integrate data collection with the existing systems at the plant. Investigating the inline weighing system at the plant revealed that significant programming would be required to extract the weight data in real-time. For this reason, it was deemed too intrusive to integrate and as such it was elected to not include weight data as part of this trial. It was assumed that the neural network would still perform effectively, with only a small drop in accuracy, without the weight information

Another challenge was later discovered in regards to labelling the training images (identifying the primal cuts in each image). The plant was able to supply a spreadsheet detailing the cut type of each primal cut passing down the line along with its registration time and weight. But it was found that this information was insufficient to uniquely identify the cut of meat in the images. One problem was that the registration time supplied was taken upstream to the camera system and given to the nearest minute. This was a problem as there were frequently more than 15 cuts of meat passing through in one minute and as such they all have the same registration time. It was also found that the order the cuts of meat appeared in the spreadsheet was not guaranteed to be the same as the order captured by the camera system; workers at Oakey Beef Exports would occasionally remove and replace pieces of meat from the conveyor for the purposes of quality control in between the registration system and the camera system. For these reasons automated labelling of the images was not possible and so manual labelling was required, and due to the time consuming nature of this task only a subset of the training images was labelled.

A general inspection of the images revealed imperfections in some images. Firstly, the positioning of the meat in the image was not consistent. In some of the images, part of the meat would be cut off at the top, bottom or sides. These images were not used as they did not contain complete information. Figure 7 shows examples of such images. Another imperfection was that multiple pieces of meat could appear in the same image. This would cause ambiguity in labelling and in training, and so these images were filtered out. Figure 8 shows examples of such images. Another imperfection was in the way the cuts of meat were presented to the camera. Some of the thinner and longer cuts would be folded or bent due to conveyor transfers before the camera. While these images would technically be valid some of them were discarded as they would cause problems in training the identification system as well as skew the identification method. Figure 9 shows examples of such images.

a) Meat cut off on side *b) Meat cuff off at bottom* *c) Meat caught on side of conveyor*

Figure 7: Meat on the edges of the image

a) Two adjacent pieces of meat *b) Two separate pieces of meat* *c) Two stacked short ribs*

Figure 8: Multiple pieces of meat in the same image

a) Folded flank steak *b) Bent and folded tenderloin* *c) Folded brisket navel end*

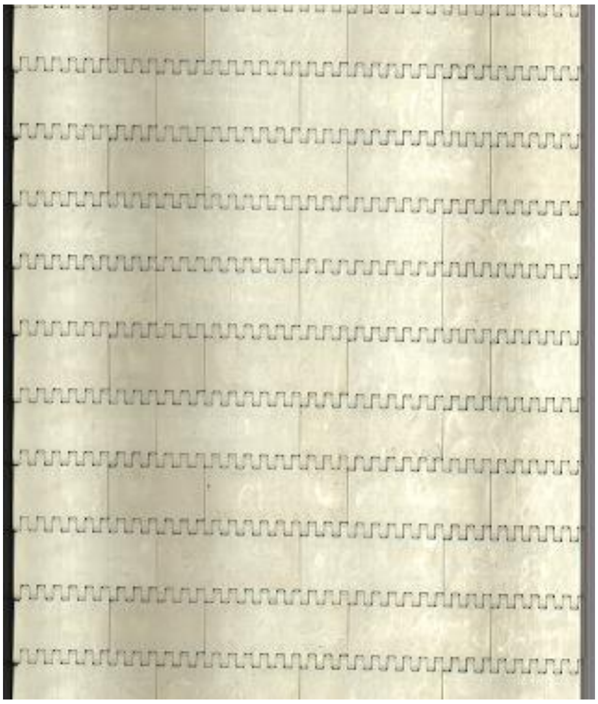
Figure 9: Bent and folded pieces of meat

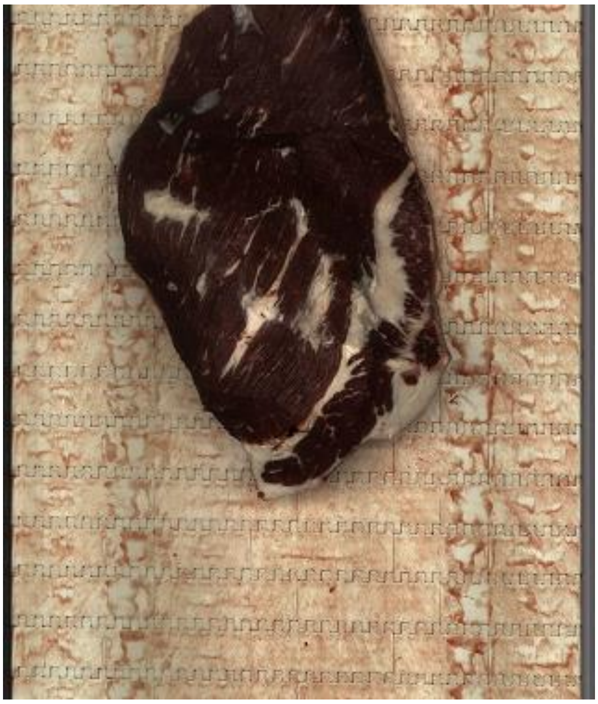
4.3.2 Training the Neural Network

Using the acquired images with the correctly identified cuts, a multilayer perceptron (MLP) feedforward artificial neural network (ANN) was used to perform a supervised learning approach to train the system to identify the primal cuts. This process was mostly identical to the one used in the previous project (2017-1064) with minor modifications so that it functioned for this trial.

Meat regioning (which is where all the pixels in the image corresponding to pieces of meat were found) needed to be changed. The in-house trial used the saturation values in the RGB rectified image to perform this which worked well since the red meat had high contrast against the background of the white conveyor. However, inspection of the images gathered during data collection revealed that the background colour of the conveyor would vary throughout the production day. At the start of the day the conveyor was white from the previous day's cleaning, but progressively became red throughout production. Figure 10 shows the state of the conveyor at various times during production. The dynamic nature of the colour of the conveyor necessitated a change in the regioning algorithm. The current regioning algorithm is based entirely on the height image. The conveyor height is determined from the image and every point higher than the conveyor is considered a piece of meat. However, this method is not as accurate as the previous method since the height data is not available at points where the 3D reconstruction cannot find a match from the master image on the slave image due to occlusion. Figure 11 shows the results of regioning with both methods.

Once the regioning was completed a feature vector (which is a collection of parameters describing the shape of the meat) is calculated. This feature vector has been modified from the previous project (2017-1064) as the weight data was no longer available to be used in this trial. All parameters related to weight were removed. To compensate, two parameters were added to the feature vector: the average height of the meat and the standard deviation of the height. The final feature vector came to be: area, width/length, fat percentage, fat bulkiness, bulkiness, compactness, anisometry, structure factor, height average, height standard deviation. A full description of these parameters can be found in the Appendix 8.3 Feature Vector Parameter Description.





a) Cleaned conveyor *b) Start of production*

c) Two hours into production *d) End of production*

Figure 10: Shade of conveyor at different times during the day

a) Colour based regioning

b) Height based regioning

Figure 11: Different meat regioning algorithms

The multilayer perceptron (MLP) feedforward artificial neural network (ANN) was developed using the Halcon software environment. The neural network was configured to have 10 inputs (corresponding to the 10 parameters in the feature vector), 12 nodes in the internal layer, 7 outputs (corresponding to the 7 primal cuts to be identified), and the output function set to "softmax" (which means the outputs sum to 1 and can be interpreted as the neural network's confidence in classification). The feature vectors of the all the training images along with their corresponding primal cut type were input into the training model. After that, automated procedures in the Halcon software were used to train and optimise the neural network.

Three neural networks were trained at various stages during the labelling process. The first two neural networks were trained from one day of images; the first one trained to identify 5 primal cuts using 303 training images and the second to identify an additional 2 primal cuts (for a total of 7) using an additional 102 training images (for a total of 405 images). The third neural network was trained to identify the same 7 primal cuts using 1169 training images which incorporated all the training images used by the second neural network. For the purposes of determining the overall success of the project, only neural network 3 should be considered as it contained all the training data. By training three separate neural networks, the effects of adding additional training images and adding additional primal cuts can be measured.

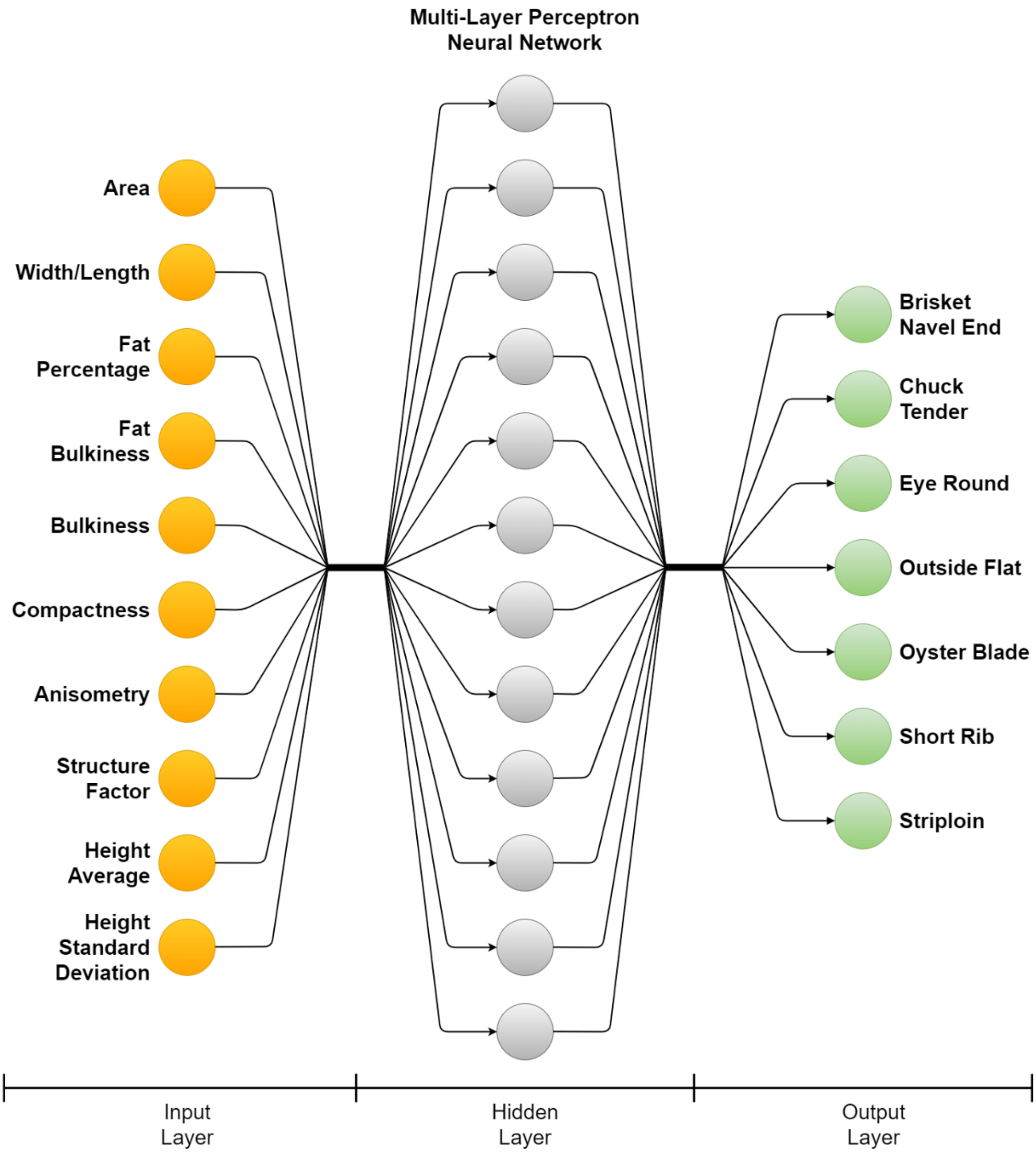


Figure 12: Multi-layer perceptron neural network

4.4 Live Trial

To perform the live trial, the image capture software was modified to incorporate the neural networks. The system performed the following steps in real time:

1. Acquire the master and slave images.
2. Compute the 3D reconstruction from the images.
3. Find regions of meat.
4. Reject any region that touch the image edges.
5. Calculate the feature vector.
6. Pass feature vector into the neural networks to acquire the identified cut type.
7. Save the images and results to a hard drive for verification.

The results were analysed after the trial was completed.

4.5 Trial Results

Three days of images (a total of 1082 images) were analysed to get the following results.

Primal Cut	Identification Accuracy
Brisket Navel End	89%
Chuck Tender	93%
Eye Round	94%
Outside Flat	87%
Oyster Blade	88%
Short Rib	100%
Striploin	90%
Total	**90%**

A more complete table of results can be found in the Appendix 8.4 Detailed Results, which breaks the results by production day and includes the counts of each primal cut. Figure 13 to Figure 19 shows examples of all the cuts being identified by the system.

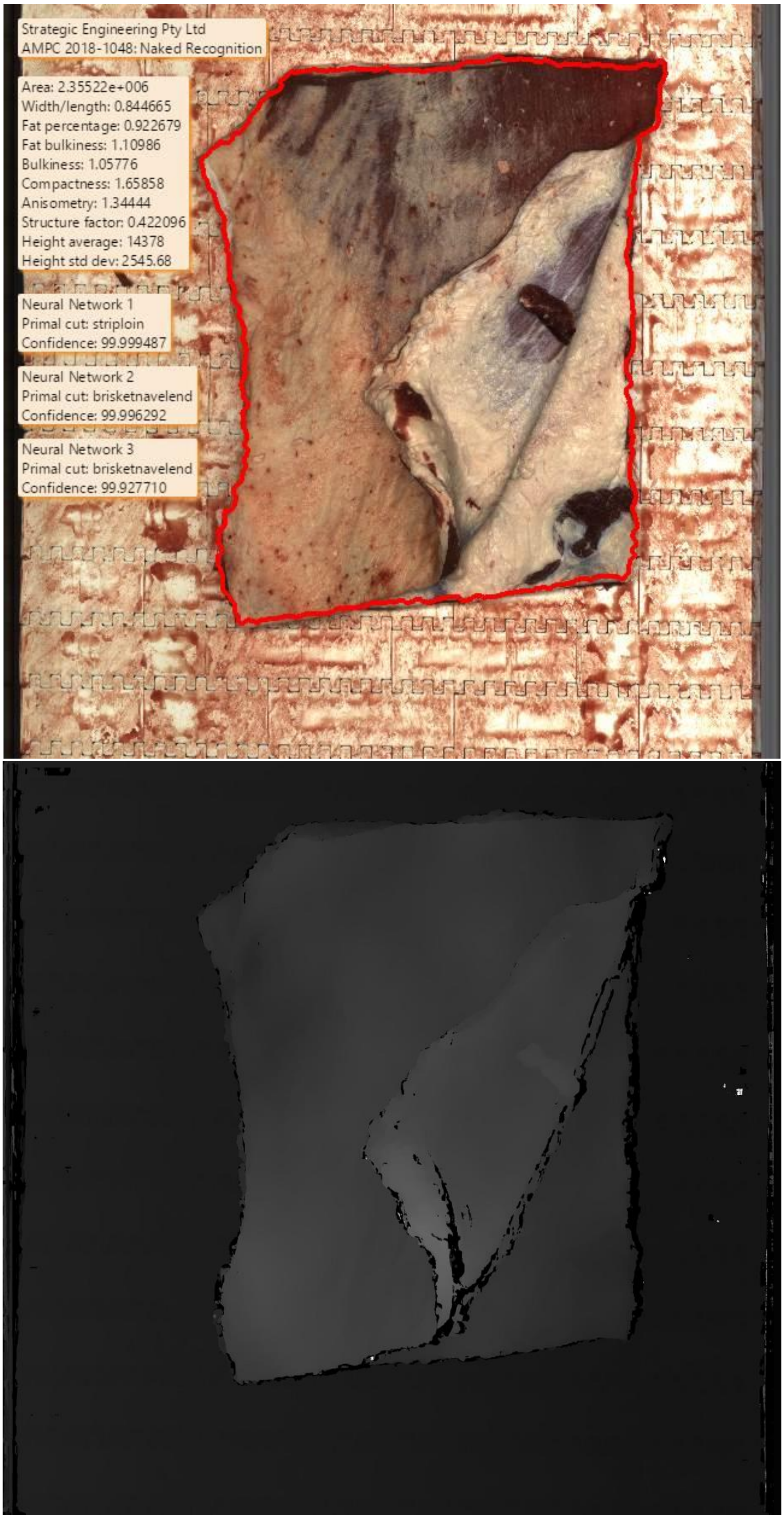


Figure 13: Brisket navel end result

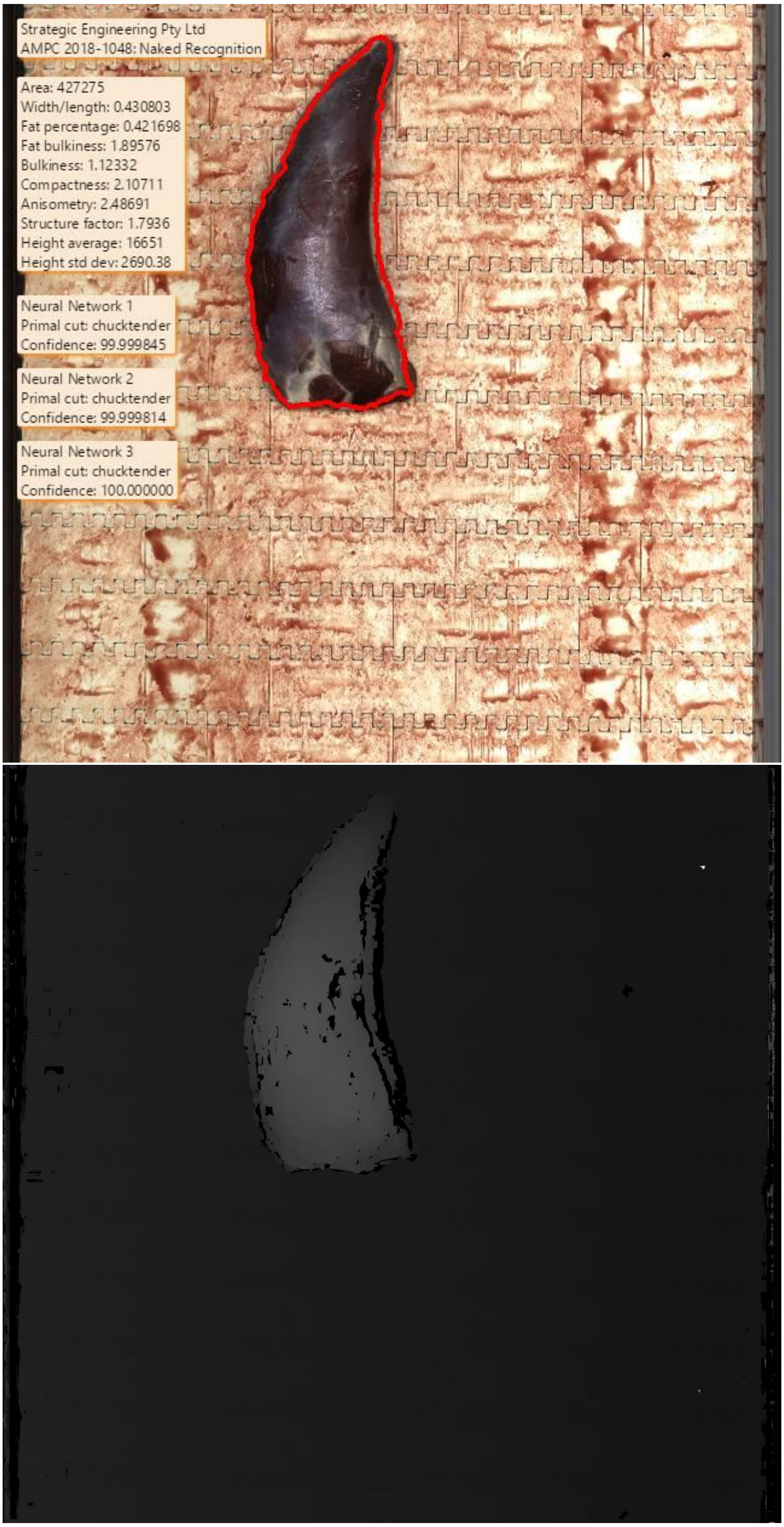


Figure 14: Chuck tender result

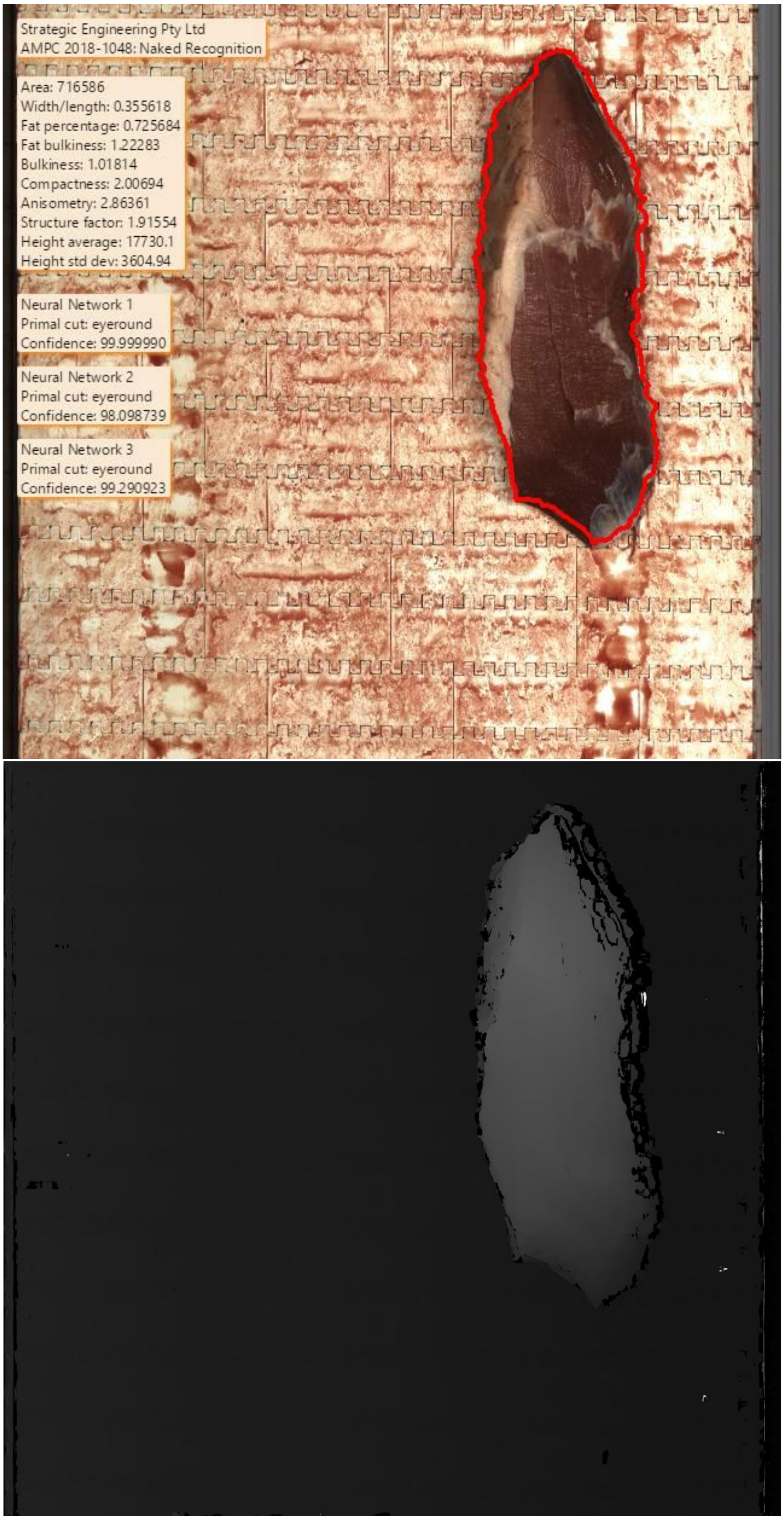


Figure 15: Eye round result

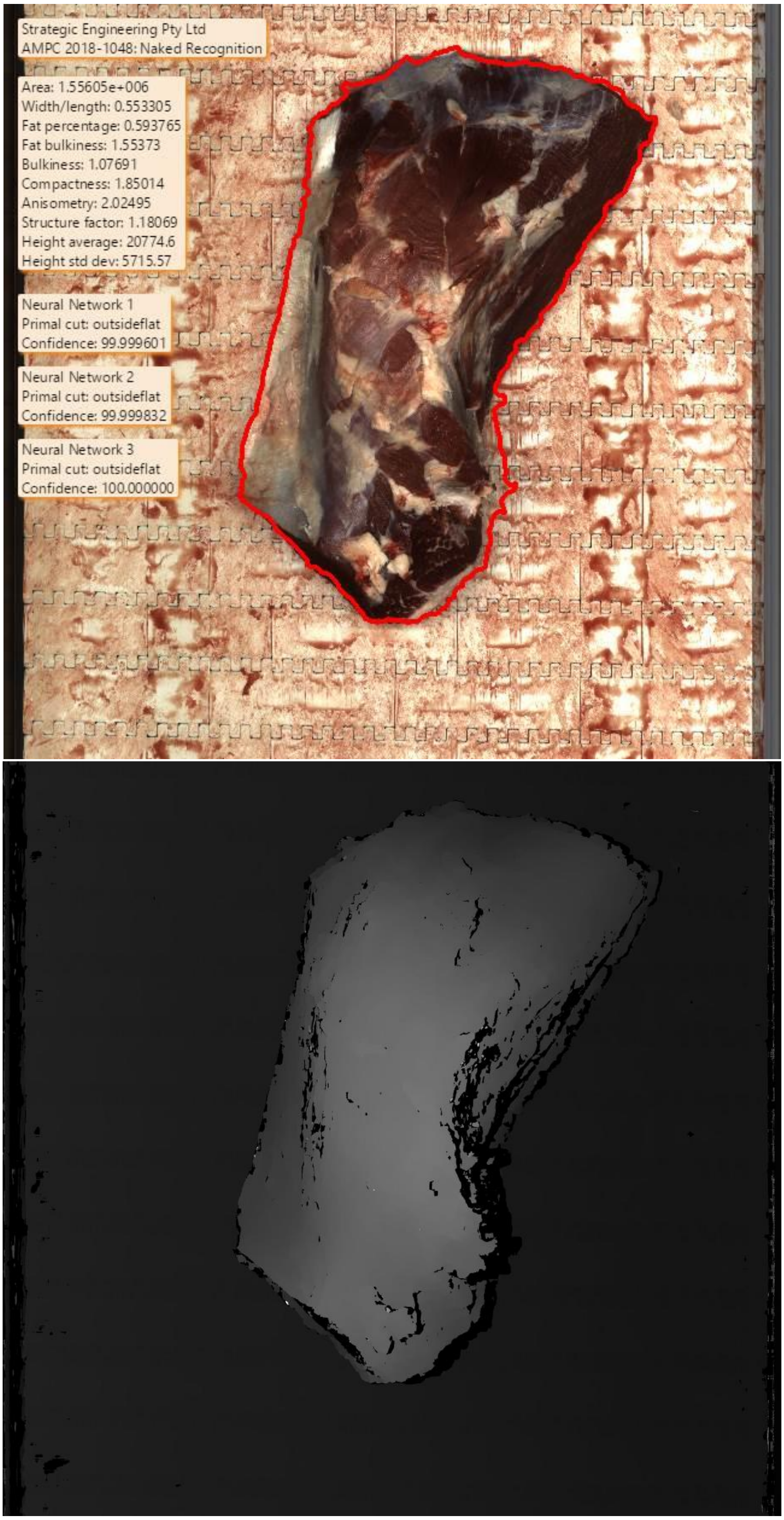


Figure 16: Outside flat result

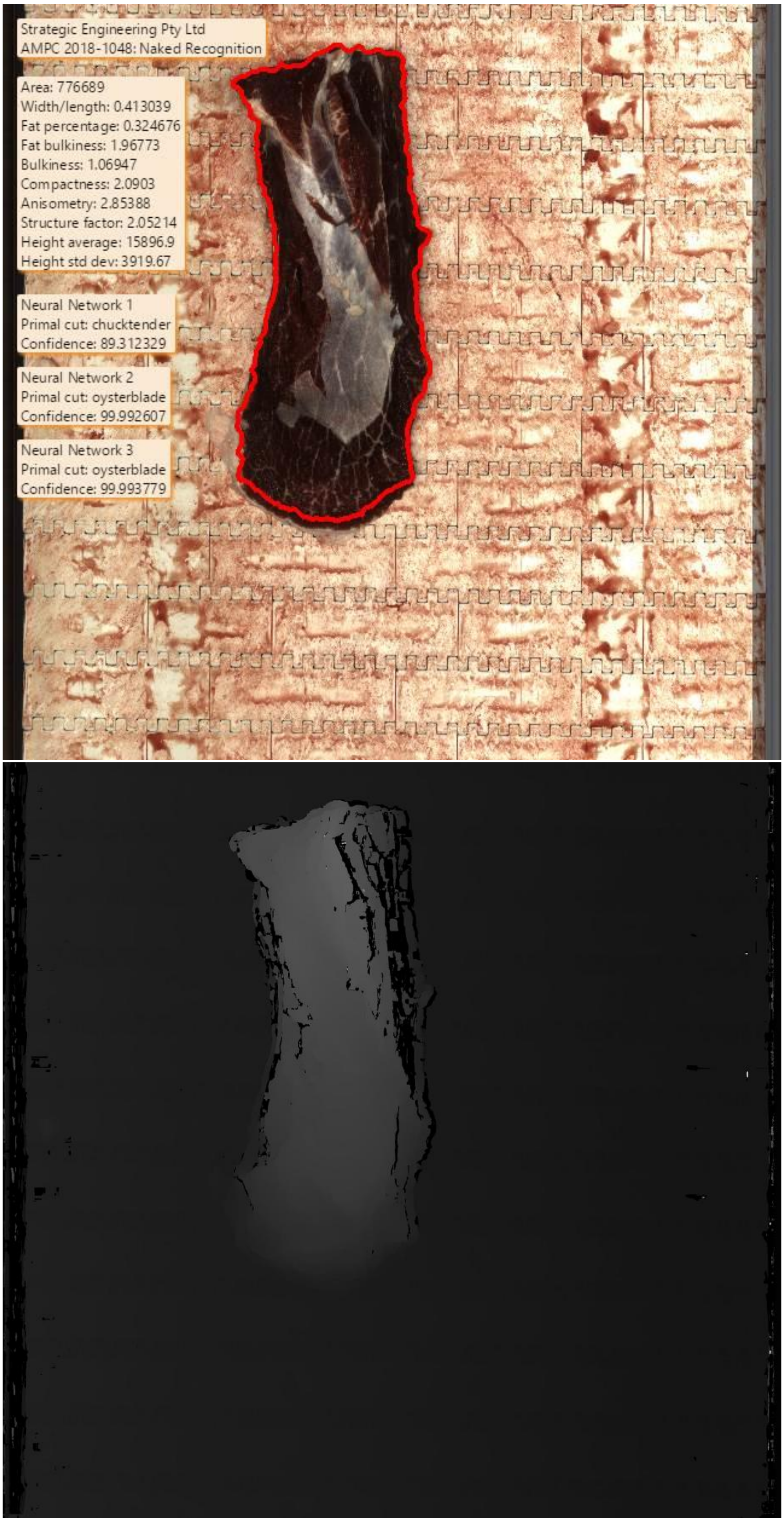


Figure 17: Oyster blade result

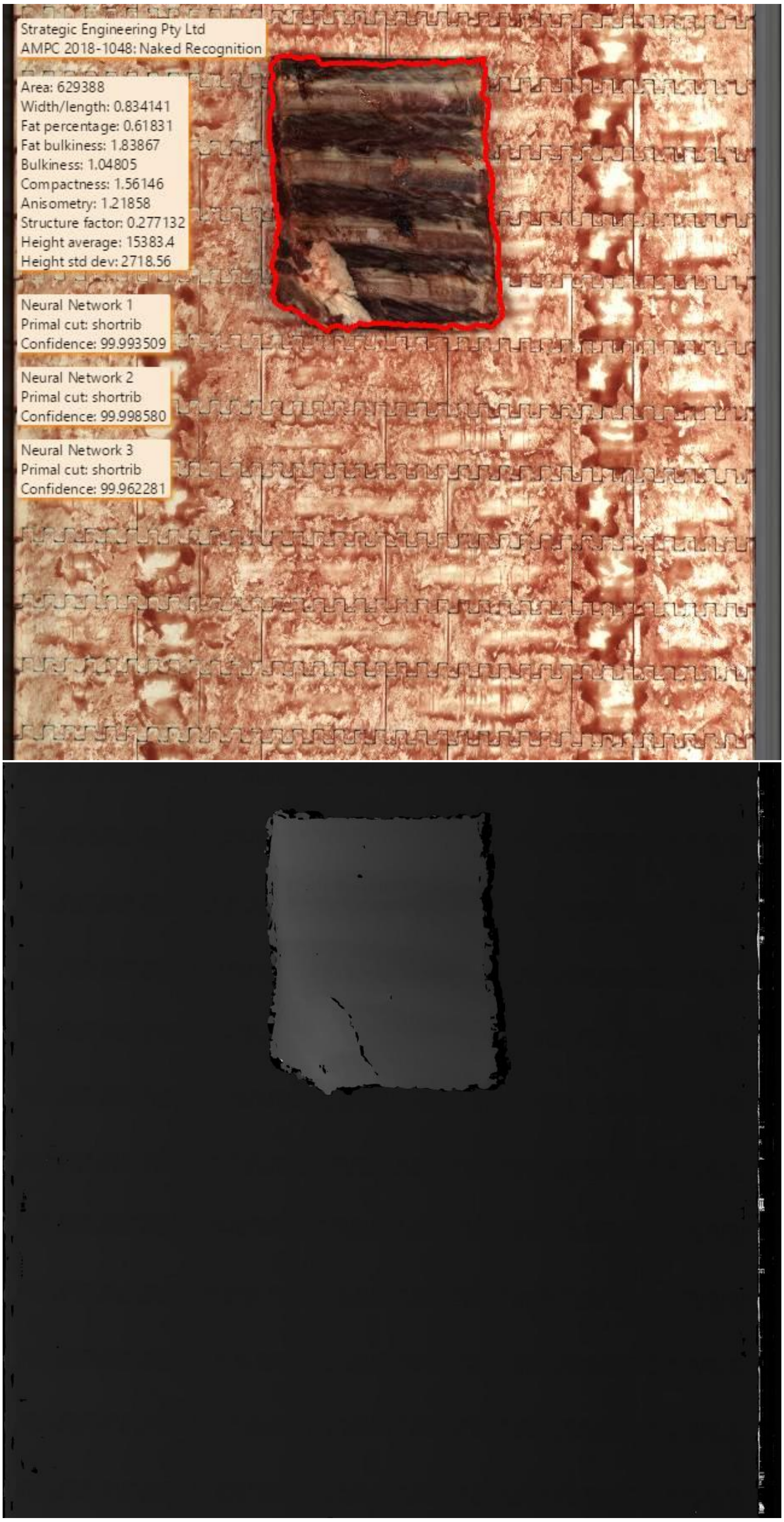


Figure 18: Short rib result

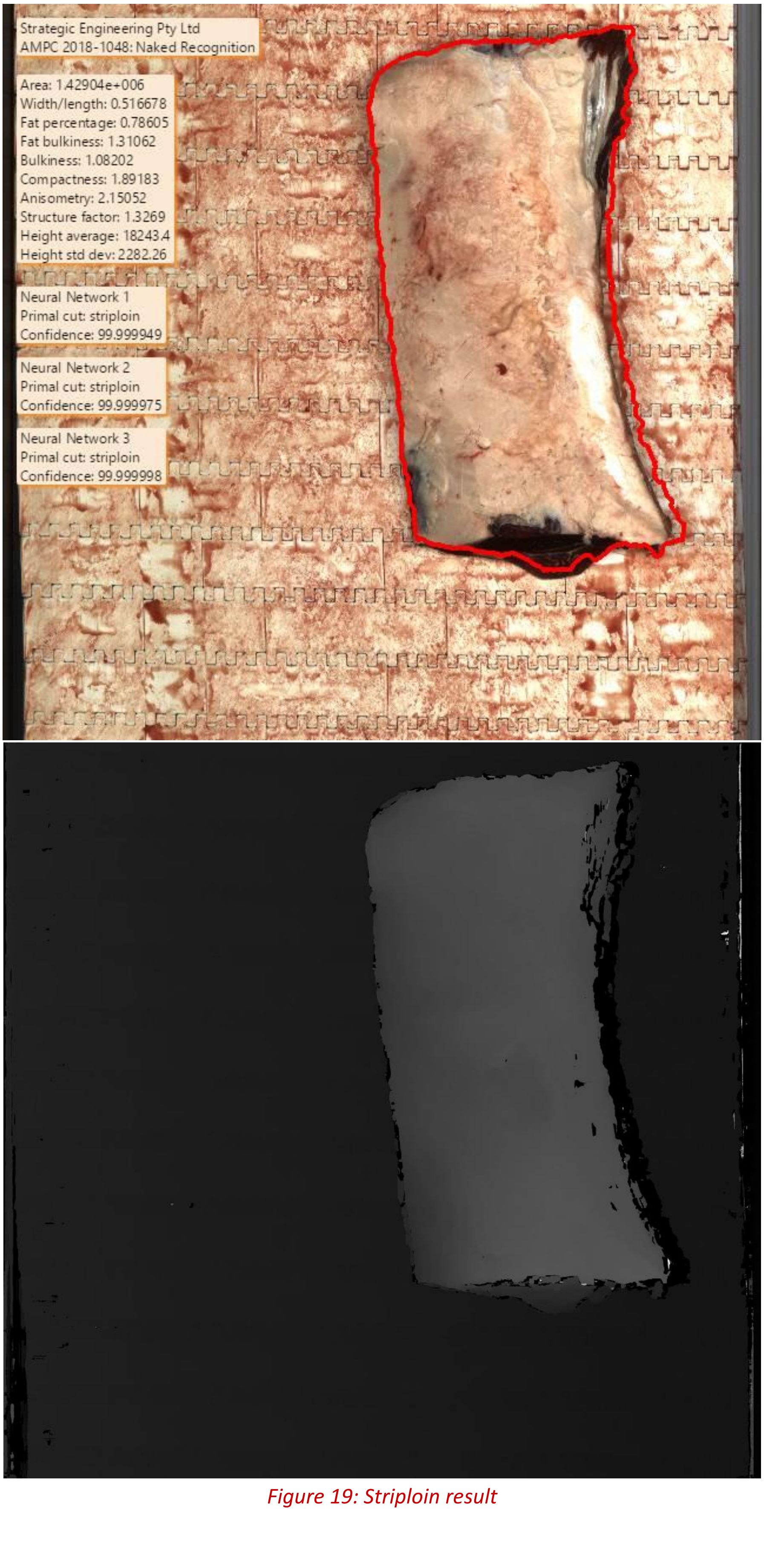


Figure 19: Striploin result

5.0 PROJECT OUTCOMES

The following outcomes were achieved:

- A suitable meat processing plant (Oakey Beef Exports) was identified to install the vision system. A suitable range of primal cuts were available with sufficient spacing between each cut and a suitable location was found which satisfied space requirements.
- The existing vision system as developed in AMPC project 2017-1064 was successfully installed at site. To do so, modifications were made in house so that the system was compliant with Oakey Beef Export's hygiene and IP specifications, then the system was transported and assembled on site.
- A neural network was trained to identify seven primal cuts using training images acquired on site.
- A live trial was successfully conducted which implemented the neural network to identify primal cuts in real time. A success rate of 90% was achieved from three days of production.

6.0 DISCUSSION

Since automated labelling of images was not possible in this trial (for reasons outlined in Section 4.3.1 Data Collection), manual labelling was required which reduced the capacity to include more training images. Additional training data would lead to a more robust neural network since a larger set of images would encapsulate more variation within each primal cut.

Compared with the in-house trial in the previous project there was more variability in how the cuts were presented to the camera. The following lists the ways that the cuts could vary and how it affected the trial:

- The thinner and longer cuts (the chuck tender, and navel end brisket in this trial) were sometimes bent or folded over due to conveyor transfers upstream from the camera. This bending changes the feature vector and may cause the neural network to incorrectly classify a primal cut. In most cases the neural network was able to correctly identify the primal cut since the training images included examples of bent and folded cuts, but it failed to correctly classify more extreme cases. Figure 20 shows an example of a folded navel end brisket.
- The size and age of the animal would affect the size of the primal cuts. The neural network was trained on three consecutive days of images so it would be likely that the training data consisted of two or three separate groups of cattle, each of different age and size. As such, the neural network may be able to classify primal cuts of similarly sized cattle with a high degree of success but not perform as well on cattle which are larger or smaller without a larger training set. This may explain the discrepancy in results on the 18th of August as compared to the other two days (a drop from 91% to 79% in accuracy as seen in the results in the Appendix 8.4.3 Neural Network 3); a visual inspection reveals that the primal cuts are generally larger on the 18th of August as compared to the other two days. Figure 21 shows an example of a primal cut imaged during data collection compared to one imaged in the live trial.

When comparing the accuracy of the three neural networks, the following observation were made:

- Comparing the first neural network with the second, a drop in accuracy from 78% to 70% can be seen. These two neural networks differed in two aspects:
  - The first neural network was trained to identify 5 primal cuts while the second neural network was trained to identify two additional primal cuts.
  - To allow the second neural network to classify the additional primal cuts, additional images corresponding to the two additional cuts were added to the training data for the second neural network.

  These differences could explain the discrepancy between the accuracy of the two neural networks; the second neural network used about the same amount of information as the first to classify an increased number of cuts which resulted in a decrease in accuracy.
- Comparing the second neural network with the third, an increase in accuracy from 70% to 89% can be seen. These two neural networks only differed in one aspect: the third was trained on roughly three times as much data as the second. As can be expected, more training data leads to increased accuracy, which can be clearly seen in these results.

- Comparing the first neural network with the third, an increase in accuracy from 78% to 89% can be seen. These neural networks differed in two aspects:
    - The third neural network was trained to identify two additional primal cuts.
    - The third neural network was trained on roughly three times as much training data.

  These results should be interpreted in conjunction with the other two points, which indicated that increasing the number of primal cuts would decrease accuracy, and increasing the number of training data would increase accuracy. As can be seen in these results, an overall increase in accuracy was seen, which indicates that the additional training data was sufficient to overcome the decrease in accuracy expected in classifying more primal cuts.

The above points would suggest that a neural would be capable of classifying the entire range of primal cuts if given a sufficiently large training data set.

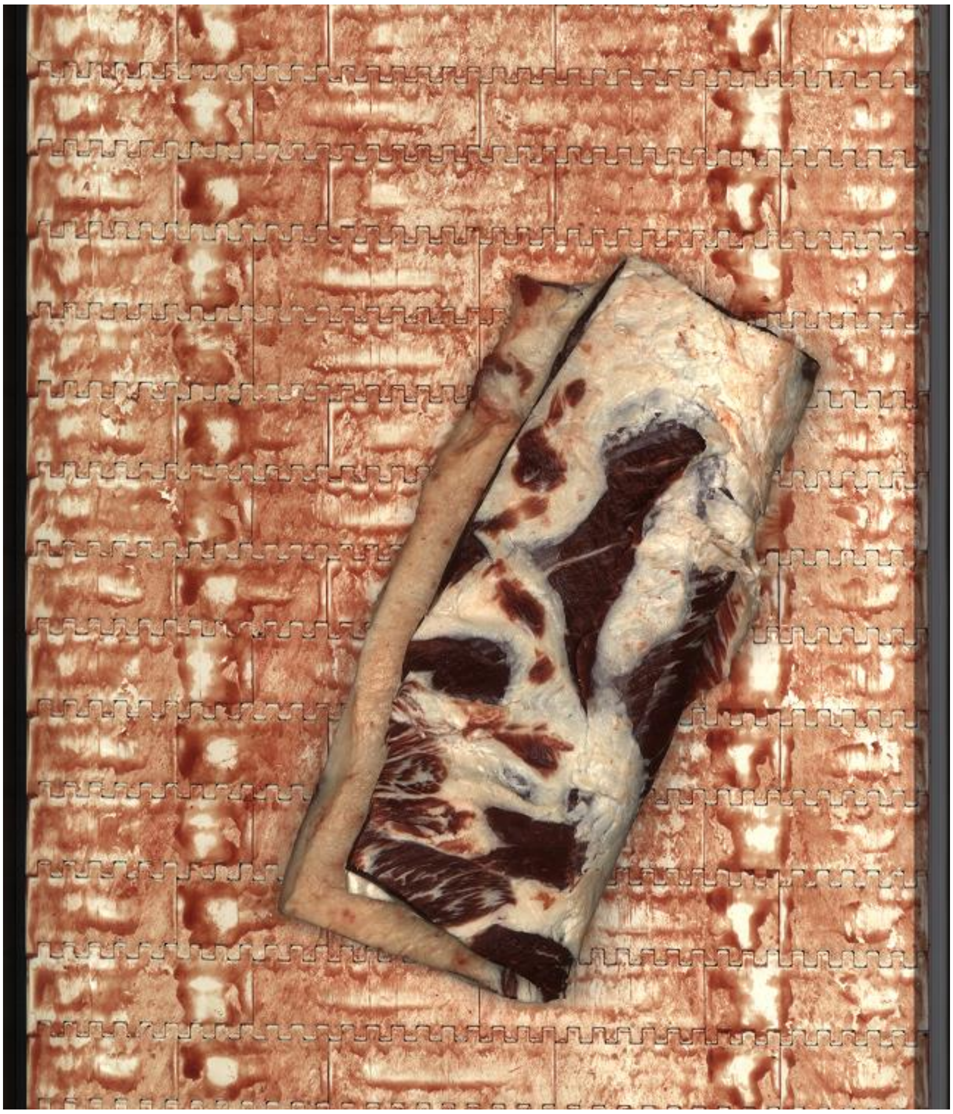
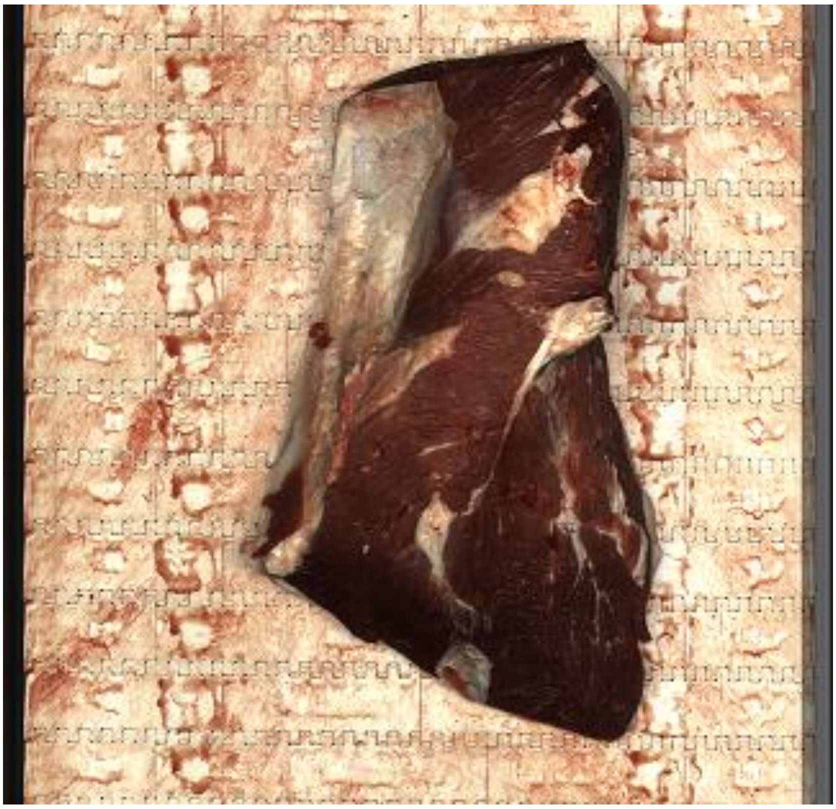


Figure 20: Folded navel end brisket

a) Outside flat in training data set



b) Outside flat in live trial

Figure 21: Comparison of outside flat during data collection and live trial

7.0 CONCLUSIONS/RECOMMENDATIONS

After overcoming several challenges during this project, the system was installed and a live trial was successfully run resulting in an average identification accuracy of 90% over the 7 primal cuts. While this level of accuracy is not sufficient for commercial applications, this project was intended to determine whether this system, which was initially developed in a workshop environment, could be integrated into an existing meat processing plant, to measure its success, to explore the challenges the system would face in a real production plant, and to find ways to improve the system. To these ends, the project achieved its objectives.

This project also enables other automation technologies such as automated labelling and bagging. Expanding the current vision system to determine the position and orientation of primal cuts from the regioning method described in Section 4.3.2 Training the Neural Network, would facilitate the progression of AMPC Project No: 2018-1049 Automation of Primal Cut Bagging. Automating the labelling process would improve the efficiency of AMPC Project No: 2018-1050 In Plant Trial of Robotic Picking and Packing System.

7.1 Suggested Next Steps

- Gain access to the existing site wide tracking and traceability system in the plant. Since this project was intended to have minimal disruptions to the host plant, access to the primal cut tracking system was not available, making automatic labelling of images not possible. Access to the tracking would greatly accelerate the process to generate training data for the neural network.

- Gain access to the in-line weighing system in plant. Access to the weight data would provide additional information for the neural network to use and would increase identification accuracy. Modifications could be made to the check weigh conveyor section developed in the previous AMPC project 2017-1064 to meet hygiene and IP standards of general meat processing plants for integration into sites without existing weight scales.

- Run a longer trial. Collecting training images and results over a longer period of time would increase robustness of the classification algorithm and confidence of results.

- Experiment with the neural network parameters. Different neural networks could be developed with varying parameters (e.g. different input feature vector, different number of internal nodes). These neural networks could be run in parallel to see which one produces the best results.

- Include information about the gross weight, age and/or breed of cattle into the neural network. Such information may improve accuracy of classification. Comparisons could be made between neural networks with and without this additional information.

- Expand primal cut range. This project looked at seven different primal cuts; the neural network could be expanded to classify more primal cuts.

- Extend the capabilities of the system to measure others characteristics such as marbling and colour for purposes such as quality control and automated grading.

- Expand the vision processing software to determine the primal cut profile, position and orientation, to allow for automated handling of naked primal cuts.
- Integrate the naked primal cut recognition vision system with automated label printing and application hardware to enable automated labelling of primal cuts.
- Incorporate the naked primal cut recognition vision system into a fully automated primal cut bagging prototype.

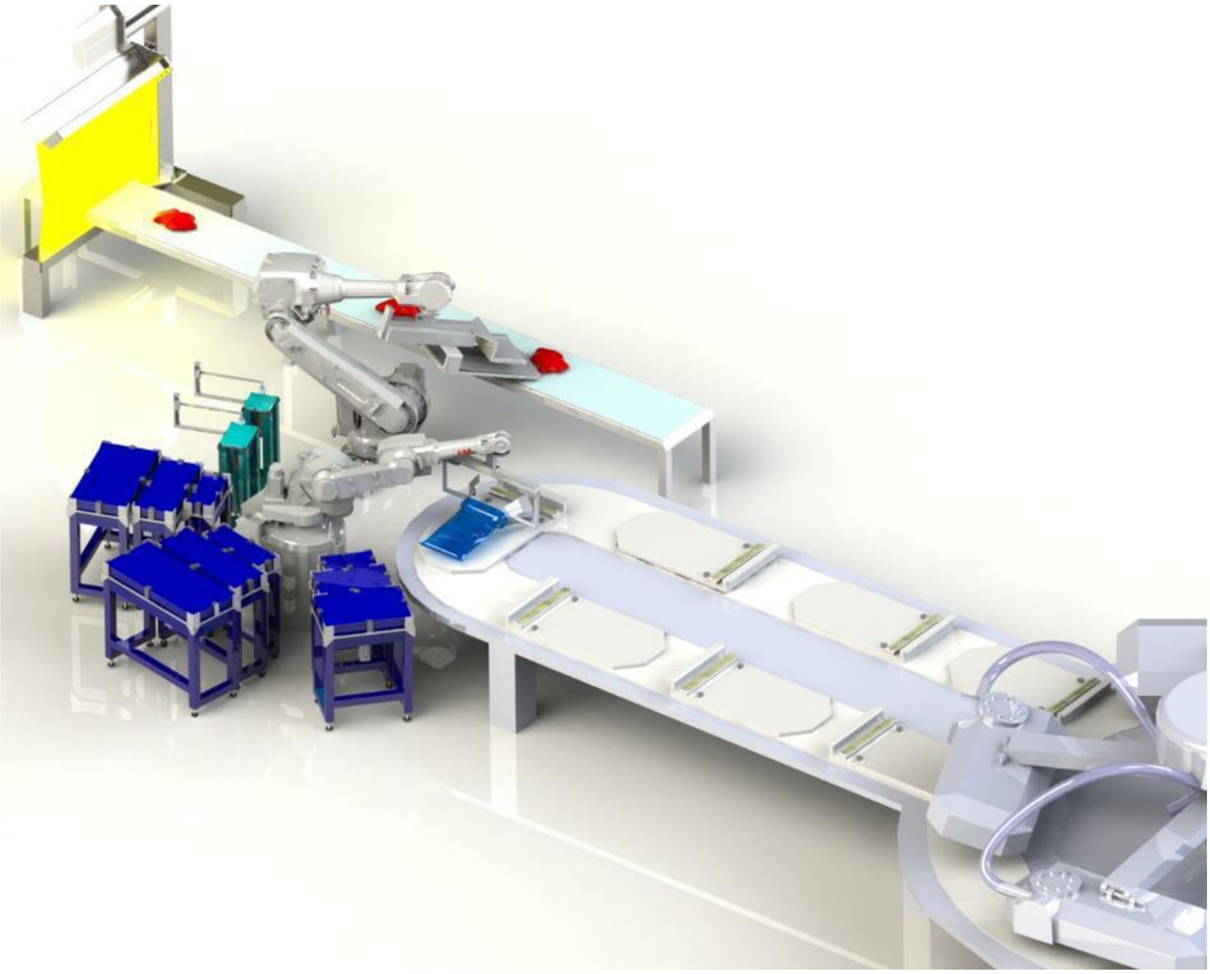


Figure 22: Concept design for a completely automated primal cut bagging system, of which the naked primal cut recognition vision system is an integral component. (Source: AMPC Project No: 2018-1049 Automation of Primal Cut Bagging)

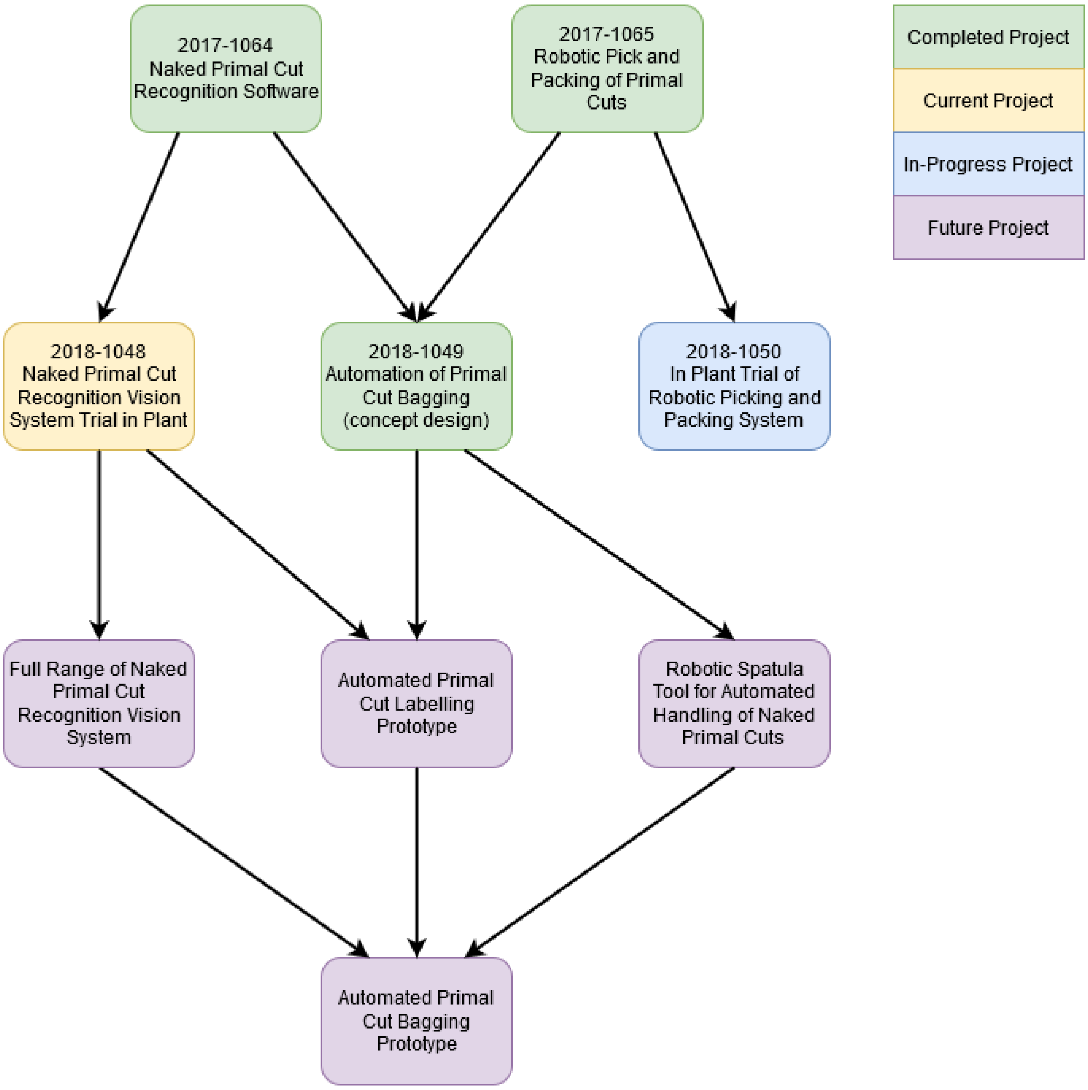


Figure 23: Project development pathway

8.0 APPENDICES

8.1 Major Hardware Components

Image	Component Name	Part
	3DPIXA Dual	Stereoscopic Line Scan Camera
	1.2m Corona II LED × 2	LED Dark Field Illumination Line Scan Light
	SICK DFS60B-S4PC10000	Incremental Rotary Encoder
	SICK W4SL-3V	Adjustable Field Diffuse Photoelectric Sensor
	HIS-ML19.5	Industrial Panel Mount Monitor and Touch Screen
	Vision PC (detailed below)	Computer

8.2 Vision Computer Components

Image	Component Name	Part
	Intel Core i7 6900k	CPU

	MSI X99A Gaming Pro Carbon RGB Motherboard	Motherboard
	NVIDIA TITAN Xp 12GB	Graphics Card
	Bitflow Dual Camera Frame Grabber; AXN-PC2-CL-2xE	Frame Grabber Expansion Card
	Corsair Vengeance LPX CMK16GX4M2B3200C16 16	RAM
	Samsung 960 PRO 500GB SSD	Disk Storage
	Corsair HX1200i 1200W 80 Plus Platinum Power Supply	Power Supply
	Noctua NH-D15 CPU Cooler	CPU Cooler
	Corsair Carbide 270R ATX Mid-Tower Case	PC Enclosure

8.3 Feature Vector Parameter Description

- **Area**
  The area of the region of meat, measured in number of pixels
- **Width/length**
  The smallest bounding rectangle which entirely contains the region of meat is found. The width of this rectangle is divided by the length of this rectangle to get this parameter.
- **Fat percentage**
  Colour analysis is used to find all the pixels corresponding to regions of fat. Then the area of the fat is found as a percentage of the area of the entire region of meat.
- **Fat bulkiness**
  The bulkiness of the region of fat. Bulkiness is a measure of how distributed the region is from the centre of the region; high bulkiness indicates the region extends far from its centre.
- **Bulkiness**
  The bulkiness of the entire region of meat. Bulkiness is a measure of how distributed the region is from the centre of the region; high bulkiness indicates the region extends far from its centre.
- **Compactness**
  A measure of the perimeter of the region relative to its area; high compactness indicates a longer perimeter relative to area.
- **Anisometry**
  A measure of how thin the region is; high anisometry indicates a thinner region.
- **Structure factor**
  A measure of how spread out along one axis the region is; high structure factor indicates more spread out.
- **Height average**
  The average height of the meat.
- **Height standard deviation**
  The standard deviation of the height of the meat.

$$Bulkiness = \frac{\pi R_a R_b}{A}$$

$$Compactness = \frac{L^2}{4A\pi}$$

$$Anisometry = \frac{R_a}{R_b}$$

$$Structure\ Factor = \frac{\pi R_a^2}{A} - 1$$

Where R_a and R_b are the semi-major and semi-minor axis of an ellipse with equal 2nd moments of area; A is the area; and L is the contour length.

8.4 Detailed Results

8.4.1 Neural Network 1

Cut Type	18/08		19/08		20/08		Total	
Chuck Tender	52/56	92.9%	99/101	98.0%	75/79	94.9%	*226/236*	*95.8%*
Cube Roll	5/32	15.6%	30/49	61.2%	68/78	87.2%	*103/159*	*64.8%*
Eye Round	11/17	64.7%	69/82	84.1%	3/3	100%	*83/102*	*82.4%*
Flank Steak	5/6	83.3%	—		62/66	93.9%	*67/72*	*93.1%*
Outside Flat	13/41	31.7%	21/82	25.6%	29/71	40.8%	*63/194*	*32.5%*
Short Rib	2/2	100%	9/10	90.0%	22/22	100%	*33/34*	*97.1%*
Striploin	41/47	87.2%	76/90	89.4%	77/80	96.3%	*194/217*	*89.4%*
Tenderloin	32/37	86.5%	70/75	93.3%	51/54	94.4%	*153/166*	*92.2%*
Total	*161/238*	*67.6%*	*374/489*	*76.5%*	*387/453*	*85.4%*	***922/1180***	***78.1%***

8.4.2 Neural Network 2

Cut Type	18/08		19/08		20/08		Total	
Brisket Navel End	15/19	78.9%	26/30	86.7%	34/36	94.4%	*75/85*	*88.2%*
Chuck Tender	24/56	42.9%	79/101	78.2%	72/79	91.1%	*175/236*	*74.2%*
Cube Roll	5/32	15.6%	10/49	20.4%	62/78	79.5%	*77/159*	*48.4%*
Eye Round	7/17	41.2%	52/82	63.4%	2/3	66.7%	*61/102*	*59.8%*
Flank Steak	5/6	83.3%	—		54/66	81.8%	*59/72*	*81.9%*
Outside Flat	23/41	56.1%	47/82	57.3%	53/71	74.6%	*123/194*	*63.4%*
Oyster Blade	38/58	65.5%	52/74	70.3%	69/82	84.1%	*159/214*	*74.3%*
Short Rib	2/2	100%	10/10	100%	22/22	100%	*34/34*	*100%*
Striploin	17/47	36.2%	65/90	72.2%	76/80	95.0%	*158/217*	*72.8%*
Tenderloin	29/37	78.4%	63/75	84.0%	50/54	92.6%	*142/166*	*85.5%*
Total	*165/315*	*52.4%*	*404/593*	*68.1%*	*494/571*	*86.5%*	***1063/1479***	***71.9%***

8.4.3 Neural Network 3

Cut Type	18/08		19/08		20/08		Total	
Brisket Navel End	16/19	84.4%	26/30	86.7%	34/36	94.4%	*76/85*	*89.4%*
Chuck Tender	50/56	89.3%	93/101	92.2%	77/79	97.5%	*220/236*	*93.2%*
Cube Roll	15/32	46.9%	46/49	93.9%	73/78	93.6%	*134/159*	*84.3%*
Eye Round	16/17	94.1%	78/82	95.1%	2/3	66.7%	*96/102*	*94.1%*
Flank Steak	4/6	66.7%	—		57/66	86.4%	*61/72*	*84.7%*
Outside Flat	37/41	90.2%	75/82	91.5%	57/71	80.3%	*169/194*	*87.1%*
Oyster Blade	55/58	94.8%	65/74	87.8%	68/82	82.9%	*188/214*	*87.9%*
Short Rib	2/2	100%	10/10	100%	22/22	100%	*34/34*	*100%*
Striploin	32/47	68.1%	85/90	94.4%	78/80	97.5%	*195/217*	*89.9%*
Tenderloin	23/37	62.2%	65/75	86.7%	51/54	94.4%	*139/166*	*83.7%*
Total	*250/315*	*79.37%*	*543/593*	*91.57%*	*519/571*	*90.89%*	***1312/1479***	***88.7%***