

# Development of Naked Primal Cut Recognition Software

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**PROJECT CODE:** 2017-1064

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**DATE SUBMITTED:** 5 October 2017

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**DATE PUBLISHED:** 6 December 2017

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The Australian Meat Processor Corporation acknowledges the matching funds provided by the Australian Government to support the research and development detailed in this publication.

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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 costs to red meat processors.

To overcome these issue and reduce production costs, a Naked Primal Cut Recognition Software Package has been developed. This solution was achieved by placing a 3D stereoscopic camera over the primal cut transfer conveyor to capture a high-resolution 3D image of each primal cut as it passed underneath. A neural network was developed to process the acquired 3D image to determine useful feature data and correctly identify the type of primal cut.

After training the system's neural network with seven different primal cuts, previously unseen primal cuts of the same type were analysed. The system was able to correctly identify all the new primal cuts and provide an identification confidence percentage, which were all above 90%. A low-value confidence percentage would flag the system to indicate a possible misidentification or unknown primal cut.

The system was developed to fit into existing plant configurations, requiring a minimal footprint. The vision camera was mounted overhead of an existing transfer conveyor and the control cabinet could be placed in a ten metre radius of the camera. Further developed of the system would increase the range of primal cuts able to be recognised. Depending on the primal cuts added to the system, additional neural network inputs may be added to the core program and the system retrained for the new parameters. This designed flexibility of the vision system significantly increases is probability of successful implementation in a commercial plant.

## 2.0 INTRODUCTION

The manual process of identifying naked primal cuts has significant costs for red meat processors. Currently, this process is labour intensive and runs the risk of misidentification and incorrect labelling of the primal cuts. The development of an automated naked primal cut recognition system would provide significant labour reductions, increased production times, and reduce the error of misidentification.

This project aims to provide the foundations to address this issue, through research and development of the best model for automatic naked primal cut identification. This includes researching the conditions in which the system will be required to run, determining the most suitable hardware, designing a mounting system to house the hardware, and developing the software package to process the data.

### 3.0 PROJECT OBJECTIVES

Objectives for the Development of Naked Primal Cut Recognition Software project are outlined below:

- To integrate 3D vision system components capable of identifying and classifying naked primal cuts.
- To develop a software package capable of determining the primal cut type, dimensions, orientation and mass in real time.
- The project aims to reduce the skilled labour costs required to identify, bag and label primal cuts and trims.
- To provide feedback to operators regarding profile parameters to refine and improve processing procedures.

## 4.0 METHODOLOGY

### 4.1 Intelligent Sensor Network Hardware and Software Architecture

#### 4.1.1 Selected Hardware Components

**Table 1: List of selected hardware components**

Hardware Component	Description
Computer	A powerful GPU is required for quick CS3D height map and rectified image generation.
Stereoscopic Camera	Stereoscopic line scan required to produce highly detailed images using a camera image width of 4K. The stereoscopic camera images are combined to generate a height map.
LED Line Light	Two LED lights required for illumination for the high-speed line scan camera capture. These lights are positioned on the leading edge and falling edge of the line scan to remove shadowing on objects.
Encoder	A programmable 10000 count incremental quadrature encoder is required for capturing with the stereoscopic line scan camera.
Load Cells System	Four load cells are used in combination to determine the weight of primal cuts on the check weight system.
Frame Grabber	Dual CameraLink (CL) cameras interface to the PC via the framegrabber PCI expansion card required for image capture.
Analog Reader	Analogue read device is used to read the voltage levels from the load cells that is later be converted into units of weight.
Photoelectric Sensor (PE)	Optical sensor used to detect an interrupt by means of object obstruction on the conveyor.

*Full list of components can be found in the appendix 9.1.*

#### **4.1.2 Hardware Communications Protocols**

##### **USB**

The load cell and PE on the check weight system interfaced into the Analogue Discovery IO USB device. It allowed for the reading of analogue inputs (load cell) and interrupting triggers on the digital pins (PE).

##### **PCI**

The encoder and PE sensors were wired into the frame grabber IO expansion card connected to the PC through a PCI connection. The raw signal information was then processed by the frame grabber and utilised by the vision application.

##### **Camera Link**

Camera Link (CL) is a serial communications protocol standard used in video products. The Chromasens camera and BitFlow frame grabber utilised this CL standard to interface together.

##### **Ethernet IP**

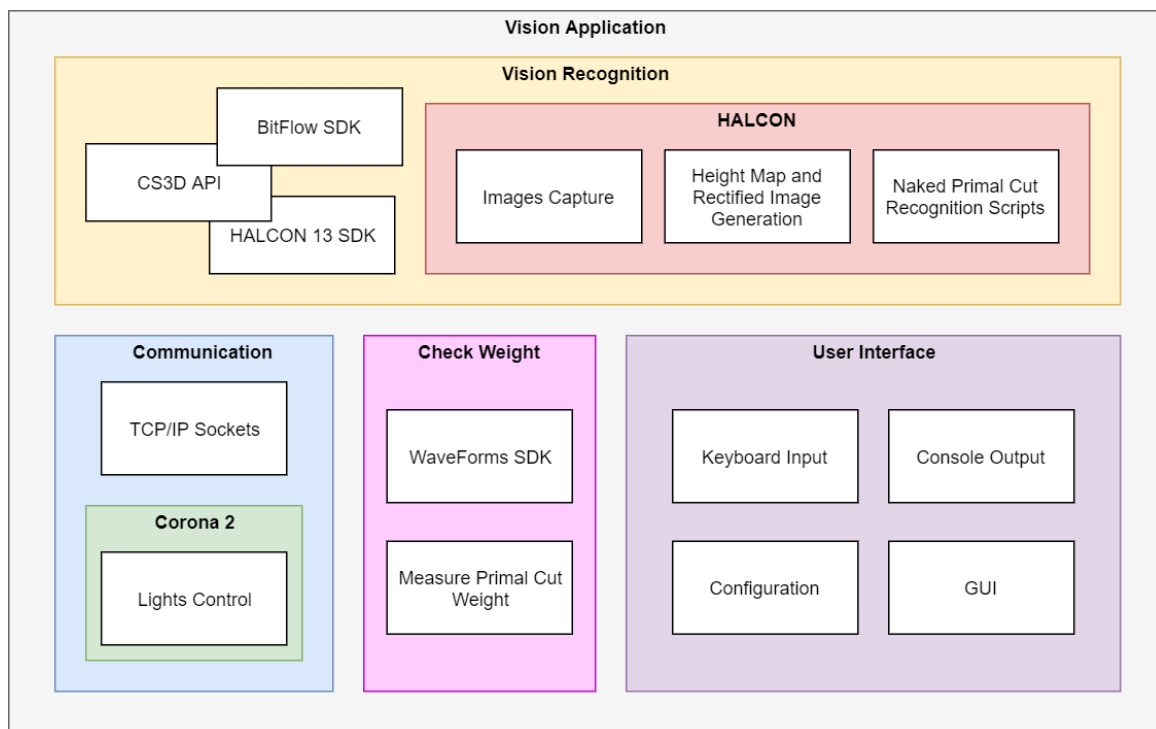
A TCP\IP socket communication was opened with the five LED light controllers to allow control over the Corona II power and current states.

### 4.1.3 Software Architecture Diagrams

The vision application was composed of four distinct components:

- Vision Recognition**  
 Handled the image capturing from the frame grabber, generating of the height map and rectified image, and image analysis and processing using the HALCON primal cut recognition scripts.
- Communication**  
 TCP/IP Sockets were required for the Corona II XLC4 state control during camera operation. The XLC4 was responsible for supplying power to the Corona II line scan LED lights for illumination of the moving stage.
- Check Weight**  
 Interfaced to third-party devices to capture the weight of the triggering item as it moved over the check weight conveyor.
- User Interface**  
 Displayed the results and allowed user input to change system parameters used during the operation of the application.

Interactions between the application components and internal submodules are illustrated in the architectural diagram shown in Figure 1.



**Figure 1: Vision application architectural diagram**



## Application Overview

The vision application consists of several stages of operation detailed below:

### 1. Initialise application functions

- a. HALCON 13
  - i. Start HDevEngine
  - ii. Load Procedures
- b. CS3D API (via HALCON Extension)
  - i. Set CS3D start parameters
  - ii. Begin CS3D image handling
- c. Framegrabber (via HALCON Extension)
  - i. Set capture frame size (length, width)
  - ii. Set capture mode (continuous grabbing with trigger)
- d. LED Control
  - i. Open socket connection
  - ii. Set to on state
- e. Check Weight
  - i. Connect to check weight device
  - ii. Zero weight

### 2. Frame capturing

- a. Capture master and slave images

### 3. Load master and slave images into CS3D API

### 4. Retrieve CS3D API output images (height map, rectified image)

### 5. Process images to determine primal cut

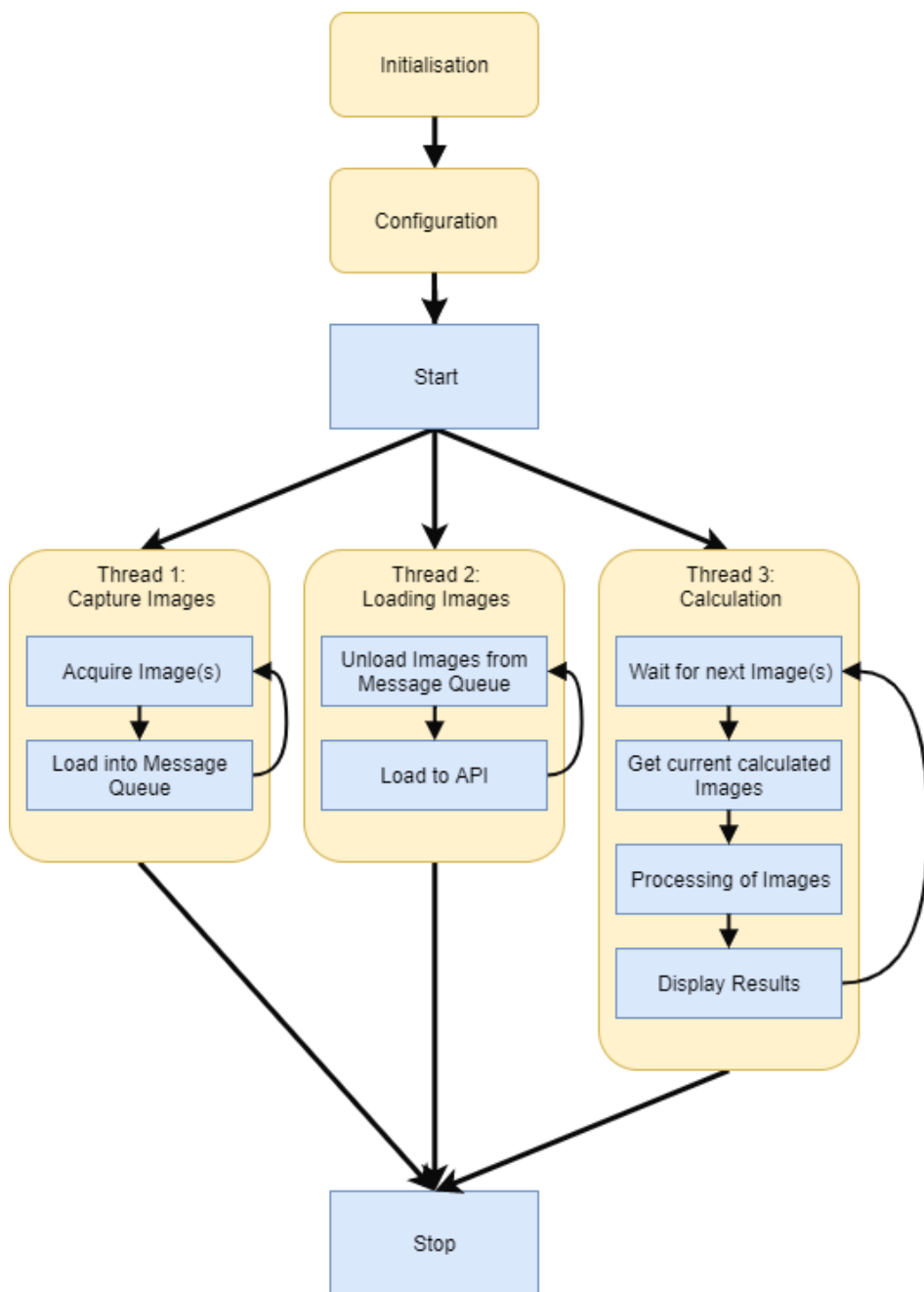
- a. Region image of the meat from the conveyor
- b. Identify meat characteristics
- c. MLP machine learning classification

### 6. Display results on screen

- a. Rectified and height map images
- b. Meat features

### Application Program Flow

The application controlled the flow of data using three threads as shown in Figure 2; one for image capture, one for loading into the CS3D API, and lastly one for unloading from the CS3D API for processing and displaying results. This multithreaded design of the application was required by Chromasens for their CS3D API solution and allowed for a higher throughput of data as the primary tasks could be parallelised.



**Figure 2: Application flow processing diagram**

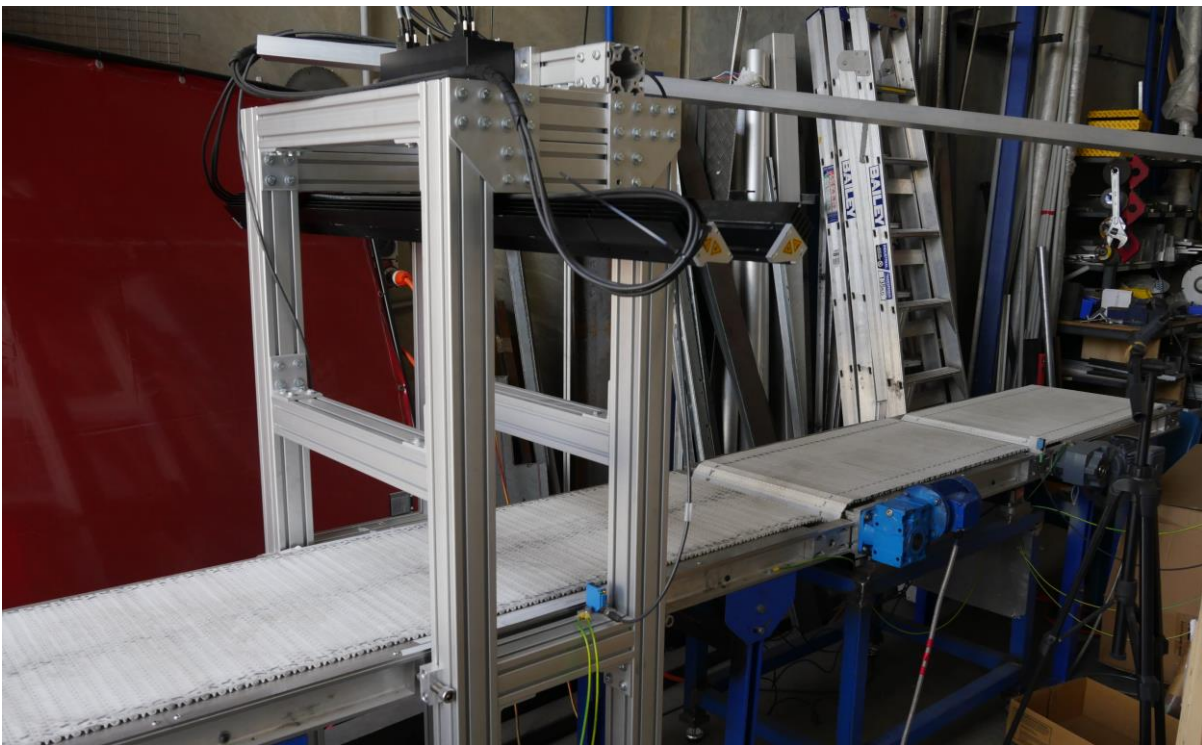
#### 4.1.4 Hardware Mounting Component Design

Due to the tight physical spacing constraints in typical commercial plants, the vision system was designed to occupy a minimal footprint. The light and camera housing frame extended 80 mm on each side of the conveyor, with the lights and camera mounted above the conveyor to maintain a compact profile.

The frame was made from profiled aluminium which allowed for quick assembly and disassembly. Due to the high precision camera utilised, the adjustable frame made it easy to calibrate the distances, angles and dimensions that were needed. With the adjustable frame, the focal point for the camera and angle of the lights could be changed so an optimal depth of image could be acquired. To aid in vibration reduction between the conveyor and the camera, the frame was directly attached to the conveyor on four points.

The LED lights were attached to an aluminium plate which was able to be rotated to a given angle. The camera was rigidly mounted to a plate on the frame, with the lenses parallel to the conveyor.

The encoder was coupled to the conveyor shaft at the motor to track the position of the conveyor while running. It was attached to the outer face of the motor with steel stand offs and then coupled to the motor shaft.



**Figure 3: Complete hardware setup**

Figure 3 shows the vision frame mounted over the conveyor. The compact design of the frame can be observed with the system itself taking up very little room in line with and above the conveyor. Meeting the tight plant design spacing requirements was achieved with the vision system hardware mounting rig.

## 4.2 Hardware Procurement and Set Up

**Table 2: Details of hardware components**

Hardware Component	Reasoning
Computer	Vision system PC is required to be powerful enough for quick generation of 3D height maps, processing and identification of the primal cut images. Each component is selected to make this process as quick as needed.
<b>Selection</b>	
Vision System PC (Appendix)	
<b>Hardware Component</b>	<b>Reasoning</b>
Stereoscopic Camera	Capable of capturing high resolution stereoscopic images for accurate meat feature identification.
<b>Selection</b>	
allPIXAPro4096	
<b>Hardware Component</b>	<b>Reasoning</b>
LED Line Scan Light	Best lighting results are achieved using the Corona II lights made by the allPIXAPro4096 camera manufacture. Lighting is needed to illuminate the scene for the sensitive line scan camera.
<b>Selection</b>	
1.2m Corona II LED x2	
<b>Hardware Component</b>	<b>Reasoning</b>
Encoder	The highly accurate encoder has been selected to provide the line scan camera with the necessary encoder stepping for line capturing.
<b>Selection</b>	
SICK Incremental Encoder DFS60 10,000 PPR	
<b>Hardware Component</b>	<b>Reasoning</b>
Load Cells System	Load cells system has a max load of 200kg needed for holding up the conveyor, the primal cuts, and other external loads. The system combines and amplifies the load cell output and the read by an analogue IO device.
<b>Selection</b>	
Bongshin DBBP series S Type Load Cell 50kg x4, Amplifier and Junction	
<b>Hardware Component</b>	<b>Reasoning</b>
Frame Grabber	Facilitates the transfer of image information between the cameras and the computer.
<b>Selection</b>	
BitFlow Dual Camera Frame Grabber; AXN-PC2-CL-2xE	
<b>Hardware Component</b>	<b>Reasoning</b>
Analog Reader	The Analog Discovery IO USB device can read analogue and digital inputs required for the inputs from the load cell system.
<b>Selection</b>	
Digilent Analog Discovery	
<b>Hardware Component</b>	<b>Reasoning</b>
Photoelectric Sensor	An industrial sensor to detect any obstruction. In this application, the sensor will be used to detect primal cuts on the conveyor.
<b>Selection</b>	
SICK Photoelectric Sensor W12G	

#### 4.2.1 Hardware Component Interface

The hardware required for the vision system was interfaced as pictured below in Figure 4, with components shown in their operating position. Additionally, the connections required for the vision system components are shown in Figure 5. This diagram details how the PC, allPIXa stereoscopic camera, LED lights and conveyor system were connected. Table 3 outlines the details for each of the line scan camera application components seen in Figure 5.

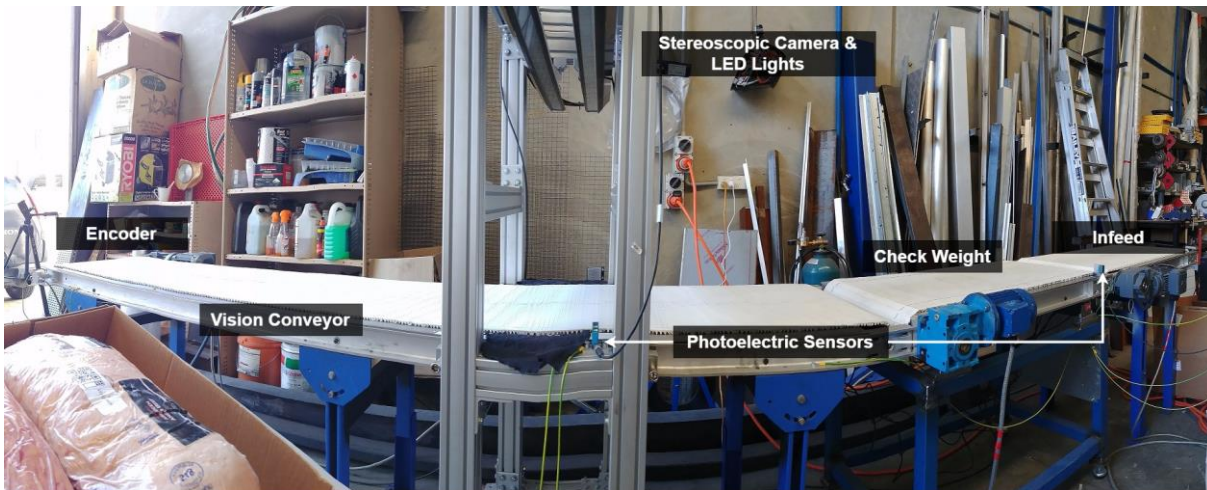


Figure 4: Integration of hardware components for the vision system

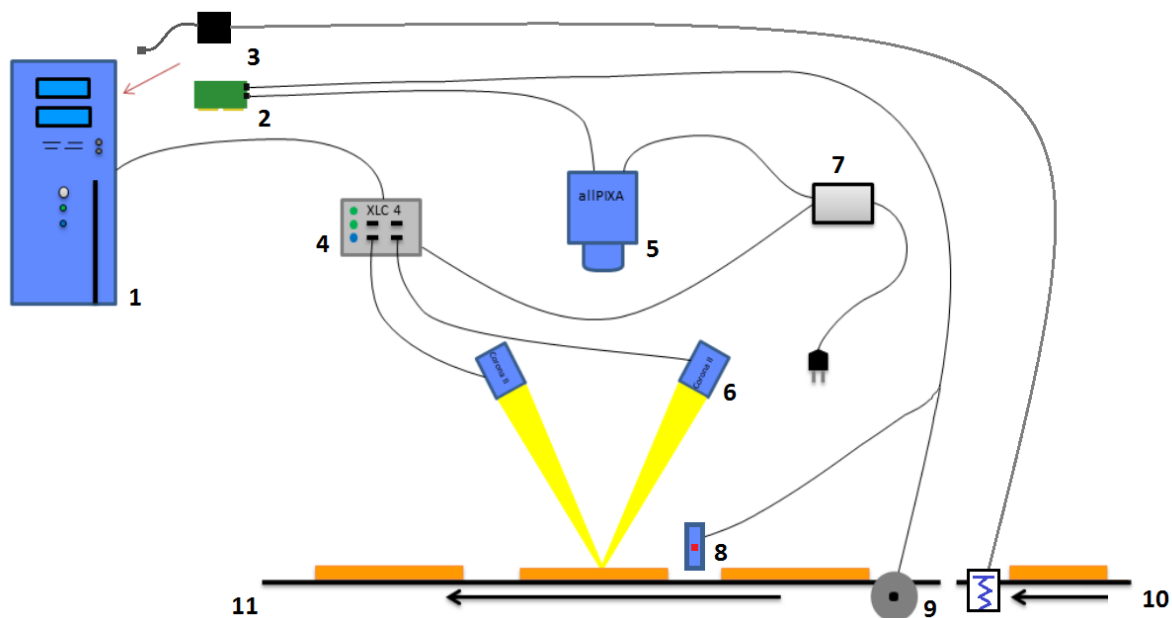


Figure 5: Interface of hardware components for line scanning camera setup

**Table 3: Line scan camera application component description**

No.	Component
1	PC: The PC system serves for a subsequent processing of the image data and controls the illumination system (4 + 6).
2	Frame Grabber (PC plug-in card): The image data is sent to the PC by means of a frame grabber with a CameraLink (CL) interface. The frame grabber establishes the necessary hardware connection to the PC (1).
3	Analog and Digital Signal Interface (PC USB Device): The Analog Discovery device measures the Analog and Digital signals from the Check Weight Conveyor (10) over a PC USB interface.
4	Illumination Controller: Controls and monitors the illumination unit. The Chromasens Corona II illumination (6) has integrated temperature/voltage sensor which can be read out with the XLC4 controller. By using the XLC4 controller, the illumination unit can be monitored and kept stable.
5	Line Scan Camera: An allPIXA camera which scans the image line by line and communicates with the Frame Grabber (2).
6	Illumination: The illumination system lights up the information scan area on the passing object.
7	Power Supply: Both, the allPIXA camera and the illumination system, require a suitable power supply.
8	Photoelectric Sensor: Detects the presence of an object using a light transmitter and photoelectric receiver. As the light beam is broken by an object the camera is triggered to begin image capturing with the Line Scan Camera (5). The Photoelectric sensor output interfaces to the camera trigger input of the Frame Grabber (2).
9	Speed detection: The speed of the conveyor belt and thus the object speed is measured with the use of a quadrature incremental encoder. The encoder is connected to the frame grabber with the appropriate inputs.
10	Check Weight: The weight of passing objects is measured and sent to the PC by means of the Analog and Digital Signal Interface device (3).
11	Conveying Unit: The conveying unit moves the scanned object past the allPIXA camera (5).



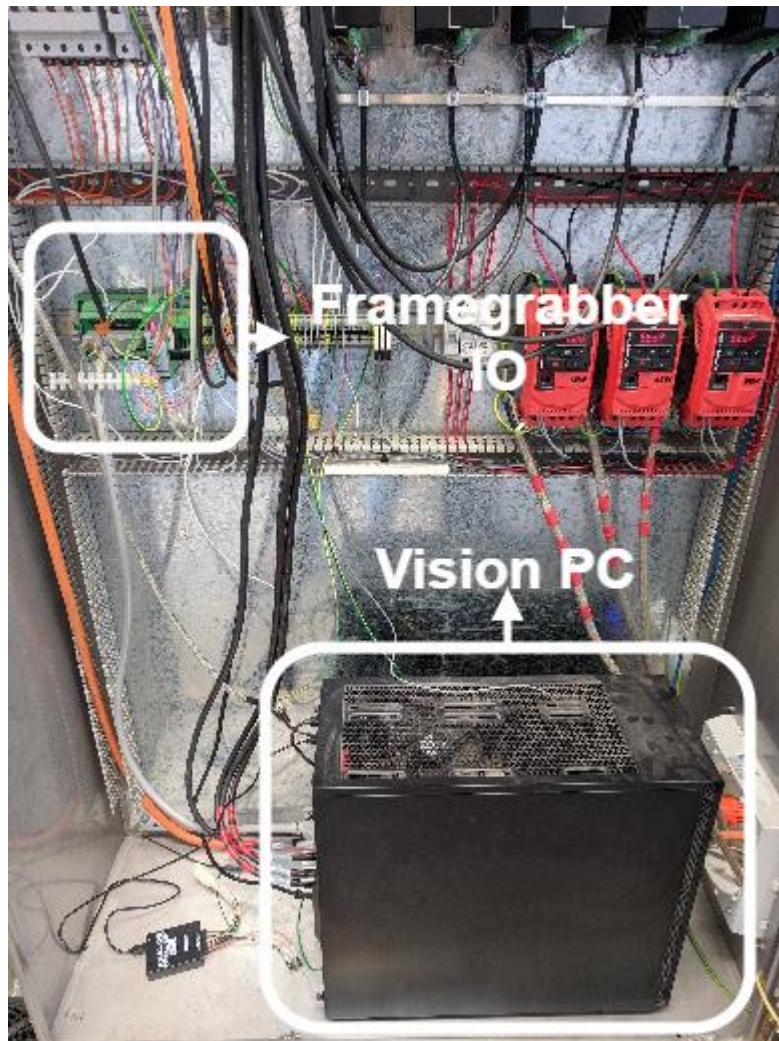
#### 4.2.2 Control Cabinet

All the system controllers and electrical components were wired inside the main control cabinet. The main components are listed below and diagrammed in Figure 6 and Figure 7

- 3 x 24V DC Power Supply Units (PSU)
- 5 x XCL4 LED Controllers
- 3 x Variable Frequency Drives (VFD)
- Framegrabber IO Board
- Vision PC



Figure 6 - Control Cabinet



**Figure 7 - Control Cabinet**

#### **4.2.3 Fabrication of Hardware Mounting Components**

The hardware components shown in Figure 8 and Figure 9 on the opposite page were fabricated for the naked primal cut vision system and are detailed below:

- **Vision Frame:**  
The frame used for mounting of the naked primal cut recognition camera and lighting hardware is shown in Figure 8. The frame was lightweight and fitted over the conveyor with a minimal footprint.
- **Camera Plate:**  
An adjustable camera plate shown in Figure 8 was fabricated to hold the Chromasens stereoscopic camera using the existing screw mounting points.



- **Light Brackets:**

The light brackets were attached to an adjustable spine mounted to the lights directly as shown in Figure 8. The design allowed for alteration of the light angles to adjust the working height of the camera.

- **Conveyor Bolts:**

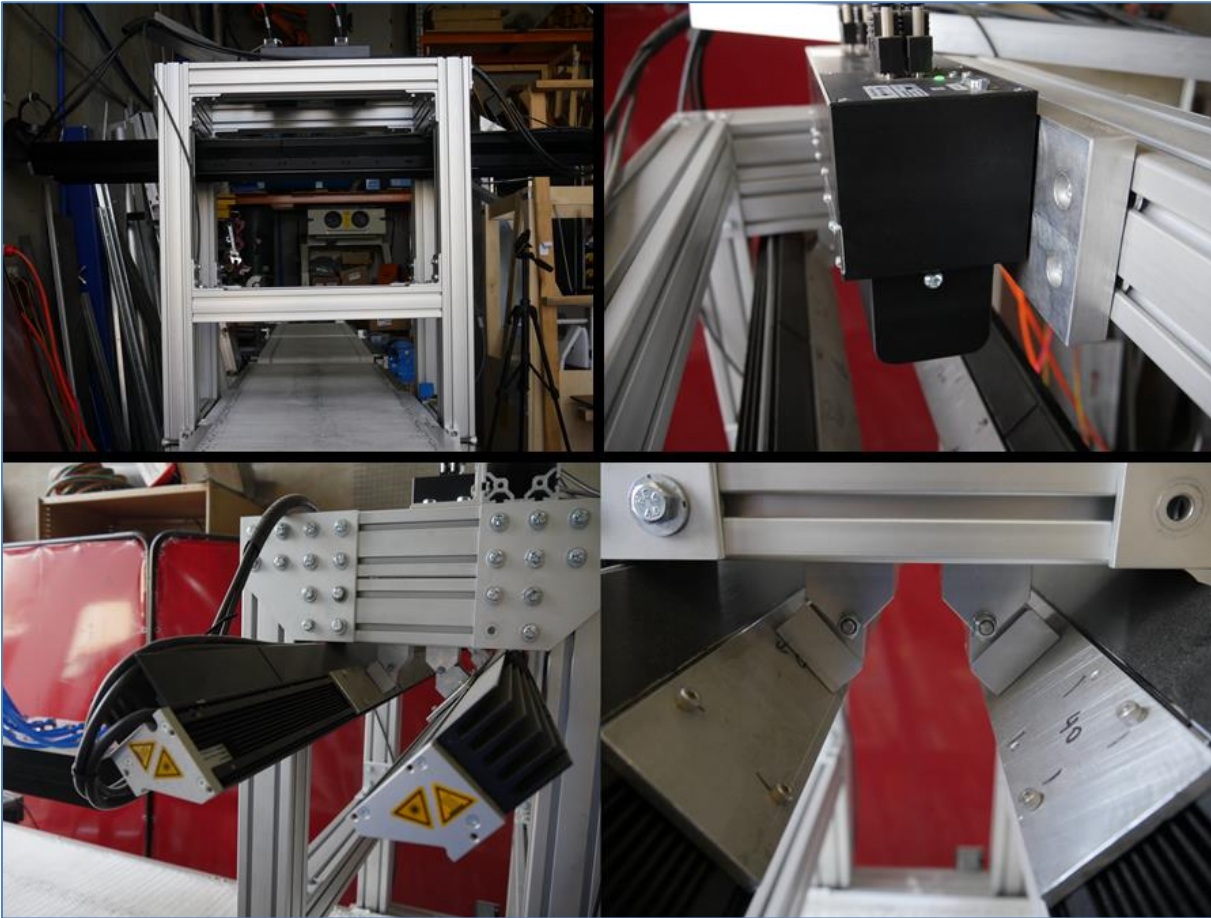
Figure 9 shows the conveyor bolts which pressed and held the vision frame against the conveyor. This reduced the amount of vibration relative to the camera required to capture a defect free image.

- **Encoder Setup:**

The quadrature encoder shown in Figure 9 was mounted on the face of the motor and was coupled to the motor shaft with a 1:1 ratio.

- **Load Cells System:**

The load cells were connected to the frame of the conveyor and a stable bottom box as shown in Figure 9. This reduced the vibration from the motor as much as possible to receive an accurate and consistent reading. Each of the four load cells were mounted to the bottom of the conveyor platform as well as to the rigid conveyor stand at the corners. Using a rigid platform for the load cells improved the accuracy and consistency of readings taken on the check weight.



**Figure 8 - System frame and conveyor (top left), camera and camera plate attached to frame (top right), lights and mounting brackets attached to frame (bottom)**



**Figure 9: Frame bolts to attach to conveyor (left), encoder setup with motor coupling and mount (middle), load cell holding up conveyor and attached to base frame (right)**

## 4.3 Software Development

### 4.3.1 Software Library Licensing

Several licenses required to run the software libraries were procured, these are:

- **HALCON 13 API (run-time dongle)**  
HALCON is a programming development environment which was utilised in this project. It was used to develop a vision application using many of the machine vision procedures available.
- **CS3D API (run-time dongle)**  
An API developed by the Chromasens allPIXA stereoscopic camera manufacture which converted raw images (master and slave) from the camera into application ready height maps and rectified images. These resulting files allowed further image processing with depth.
- **BitFlow SDK**  
SDK for the BitFlow framegrabber capture card allowed for integration into the PC application environment via CameraLink camera cables and PCI framegrabber.
- **WaveForms SDK**  
WaveForms SDK was required to write the modules necessary for interaction with the Analogue Discovery USB device used to read the connected analogue outputs and trigger pins for the check weight system.

## 4.3.2 Software Module Development

### 4.3.2.1 HALCON Image Acquisition

The HALCON development environment was used to create a module for the acquisition of images using the inbuilt frame grabber functions. The images are transferred into the vision PC Application via the BitFlow frame grabber card. This frame grabber connects to the allPIXA stereoscopic camera and to the photoelectric sensor as an external camera trigger. When the external trigger was engaged by a primal cut passing under the camera along the conveyor, the frame grabber triggers the camera to start capturing rows of images for a fixed distance of travel. These lines are combined into an image and the frame grabber makes these accessible to the image acquisition module. As the camera is stereoscopic, both cameras captured an image at the same time and each image is sent to the frame grabber. These images are known as the Master and Slave images.

### 4.3.2.2 HALCON Rectified and Height Map Generation

A HALCON module was created to process the raw master and slave images, into a rectified image and a 3D height map. The Chromasens CS3D API was used for the generation of this data. This module takes the raw master and slave image data from the image acquisition module and sends the images along with configuration settings to the CS3D API for processing. Master and Slave image example are shown in Figure 10. The CS3D API generates and returns a rectified image (Figure 11) and a 3D height map (Figure 12). The CS3D API makes use of dual graphics cards inside the PC to achieve a fast processing time of less than four hundred milliseconds. A rectified image is the result of merging the master and slave colour images, into one centred image. The height map is a single channel grayscale image, each grey value pixel represented the vertical distance from the camera lenses to the height at that point of the image. Figure 10 show examples of the Master and Slave Images



Figure 10: Master and Slave Images

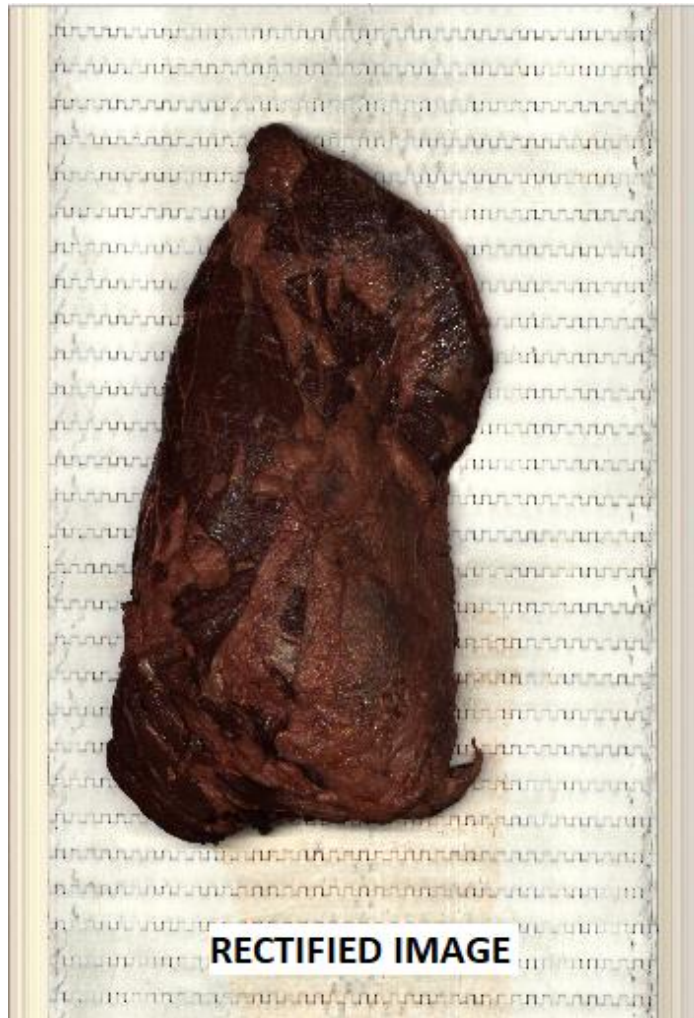


Figure 11 - Rectified Image





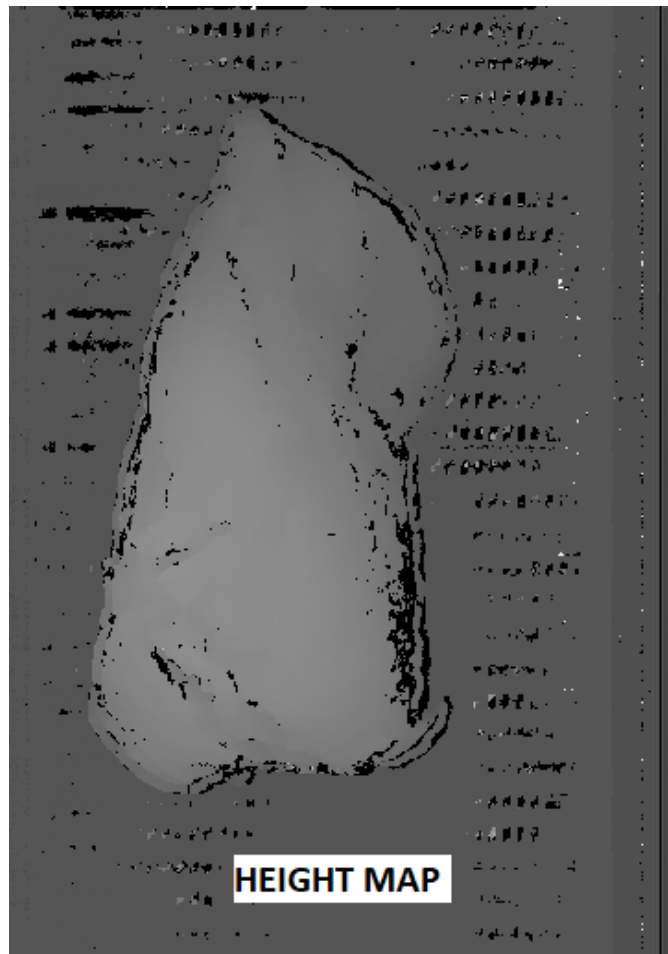


Figure 12 - Height Map

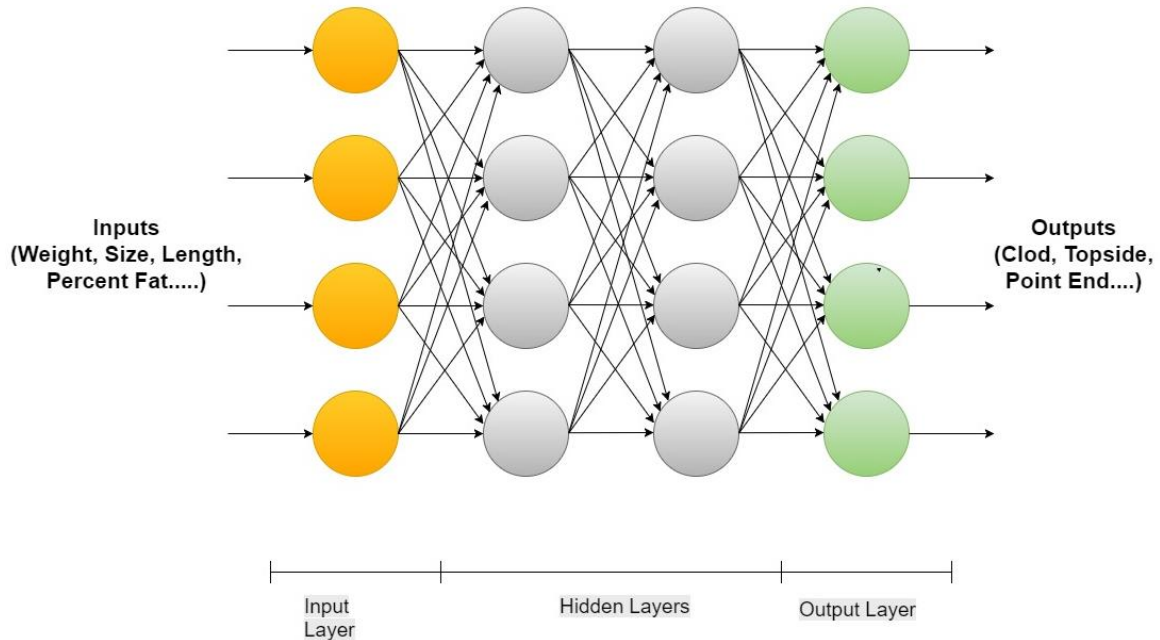
#### 4.3.2.3 HALCON Image Recognition Module

Initial research was conducted on several forms of classification techniques to determine a suitable approach for the identification of the naked primal cuts. Multi-Layer Perceptron (MLP), Support-Vector Machines (SVM), Gaussian Mixture Models (GMM), and K-Nearest Neighbours (K-NN) were all considered for this process.

MLP classifier is suited for high-speed classification but requires an offline training process that is slow. However, it has fast classification time, high accuracy and no limit to the amount of input layers. SVM classifiers can perform with a higher accuracy than most classifiers but this comes with a dramatically slower processing time, as they also require a large amount of memory available. GMM classifier is very fast for both training and classification, however, it is limited by how many distinctive features it can use for classification. K-NN classifier is fast for both training and classification, can handle a large amount of input features, but requires substantially more memory to process the data and the accuracy is not as high as the other mentioned classifiers.

From the research conducted on different forms of classification, it was determined that utilising an MLP Neural Network Model would best suit the requirements for identifying primal cuts from 3D image data, high-resolution colour images, and weights of the primal cuts, with a large amount of input features and fast classification time. MLP consists of an Input Layer of identifying features, Hidden

Layers for processing the data, and an Output Layer for each type of primal cut. A visual representation of this can be seen below in Figure 13: Multi-Layer perceptron.



**Figure 13: Multi-Layer perceptron neural network**

The primal cut identification algorithm was programmed using the HALCON development environment. Image processing was used to produce identifying features of the primal cuts. To determine the identifying features, first the region of the primal cut must be extracted away from the conveyor belt. This process is completed using colour image analysis along with extracting height map data for areas over a certain height. With the region of interest found, the region of fat can then be determined using colour image analysis. This is shown in Figure 14 below.

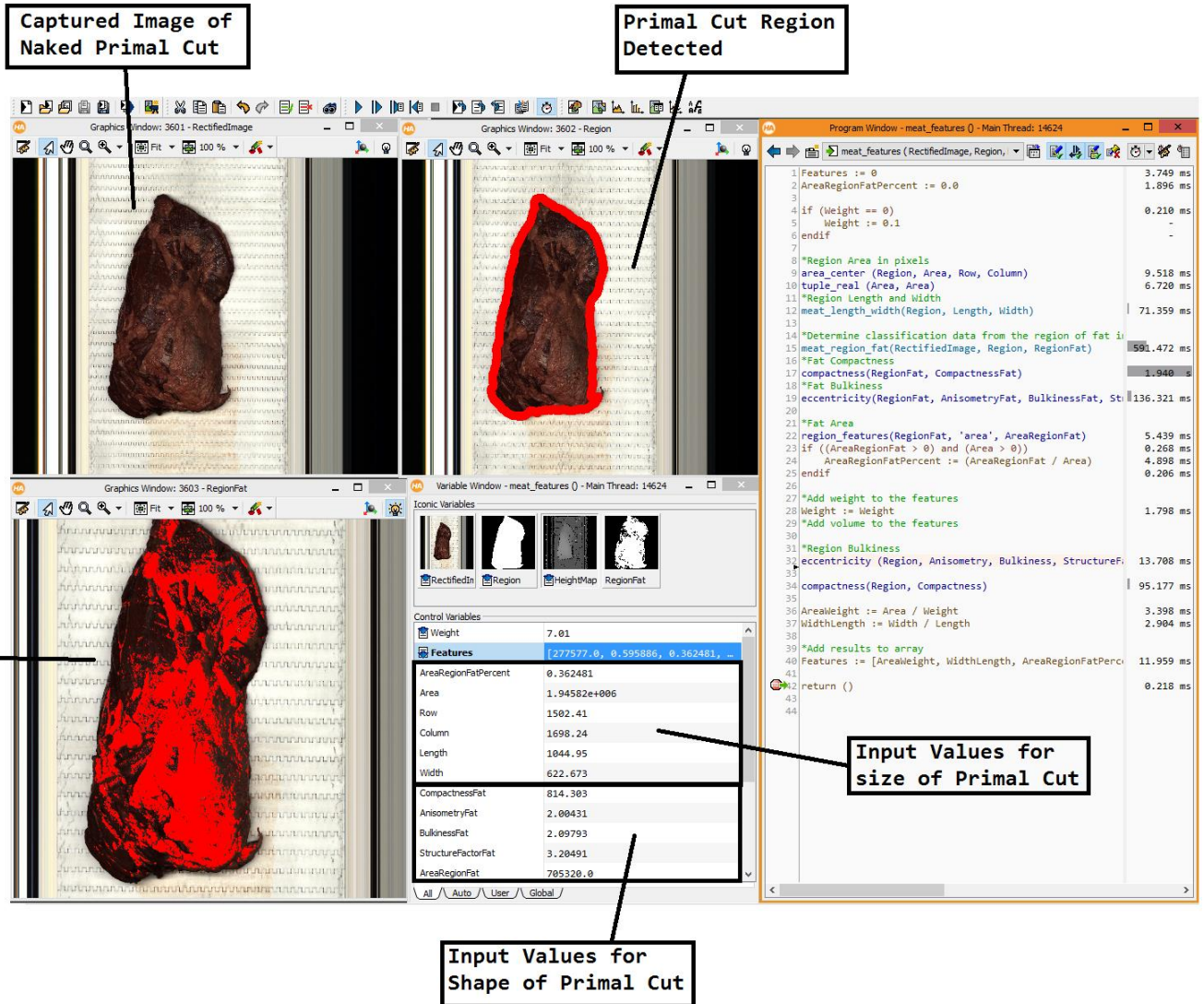


Figure 14: HALCON development environment



#### 4.3.2.4 HALCON MLP Neural Network Input Layer

The MLP Input Layer Feature values were then determined on the shape of both the fat and of the whole region of the primal cut. The features which made up the MLP input layer include:

- **Area**

Area is calculated from the region found of the primal cut, this area is measured in the number of pixels within the region. This region is shown below in Figure 15

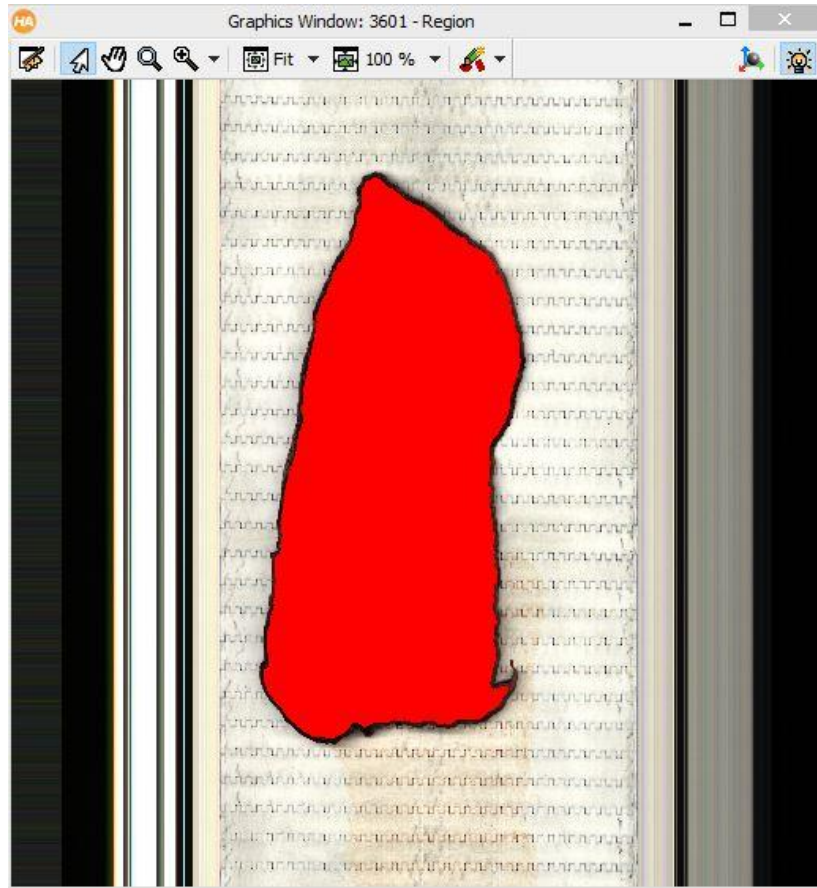


Figure 15 - Area of Region

- **Length and Width**

Length and Width measurements are taken from the region these values are measured in the number of pixels across. Length and Width is calculated using an HALCON internal function that surrounds the region with the smallest possible bounding box. The size of the length and width of this bounding box are then used as the regions length and width. Figure 16 shows an outline of the bounding box, surrounding the outlined region.

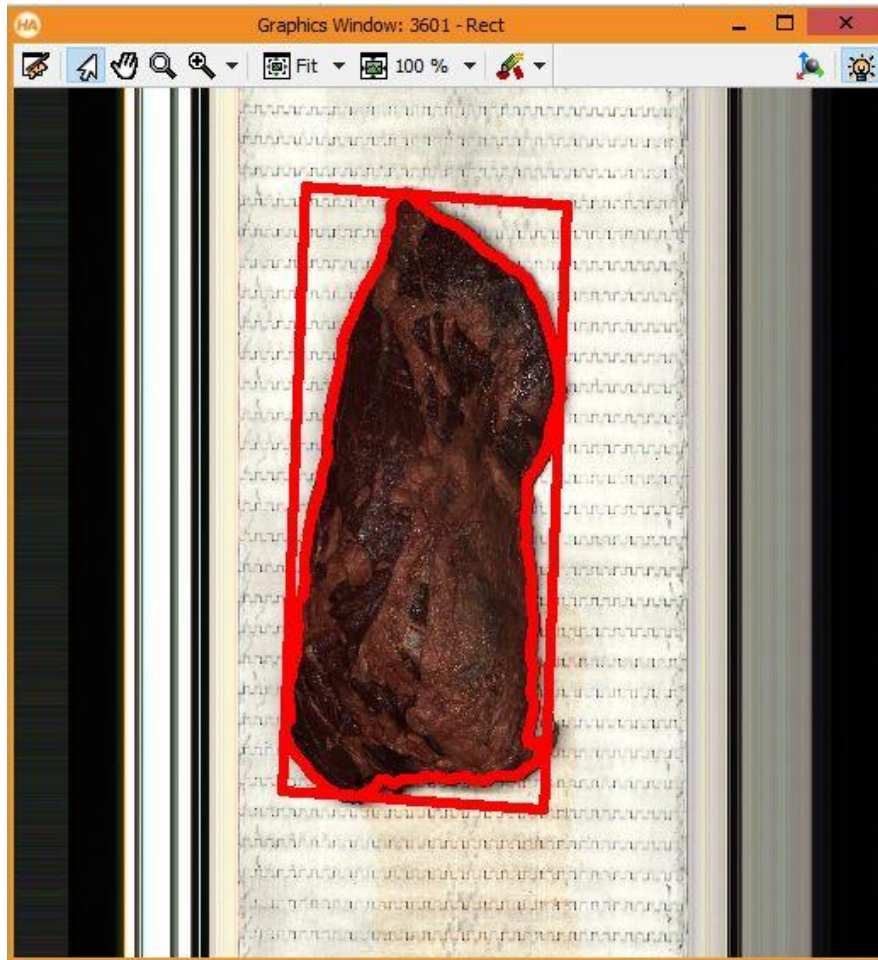
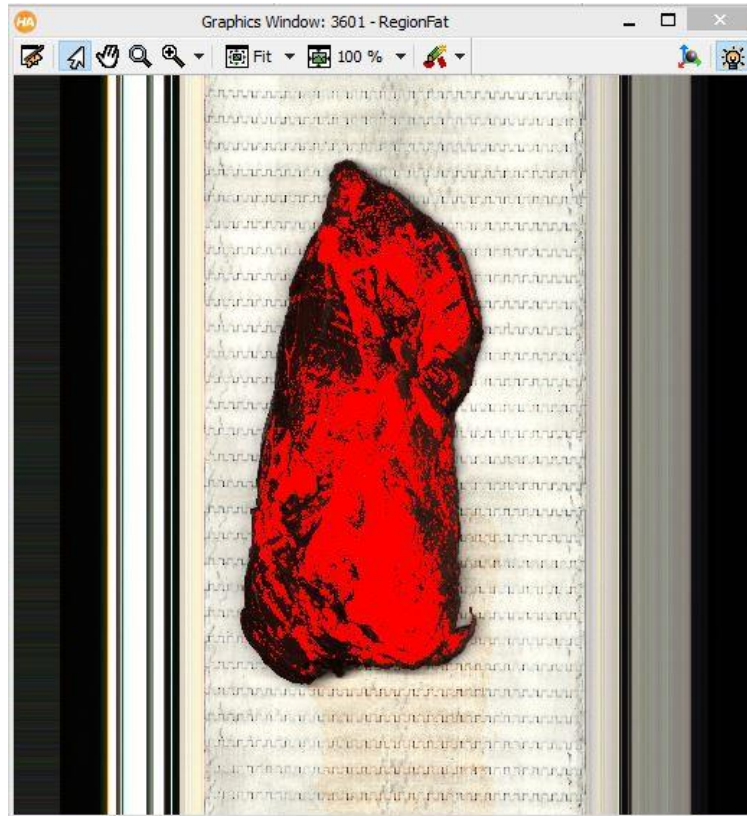


Figure 16 - Region of Interest Length and Width

- **Percentage of Fat**

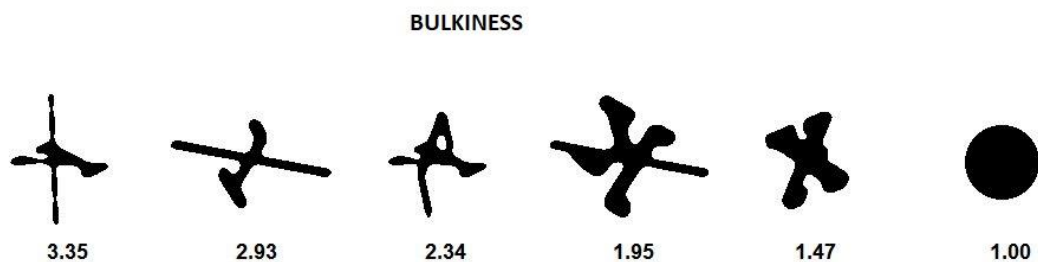
The region of fat of the primal cut is found using colour image analysis on the rectified image. The area of this fat region is then found as a percent against the whole primal cut region that was previously identified. Figure 17 shows the area of fat region marked in red.



**Figure 17 - Region of Fat**

- **Bulkiness**

Bulkiness is a measurement of a shape based on how bulky the shape is. Figure 18 is a visual representation of different regions and the value of bulkiness for each shape. The bulkiness value used for the neural network is based on the value for the whole primal cut region.



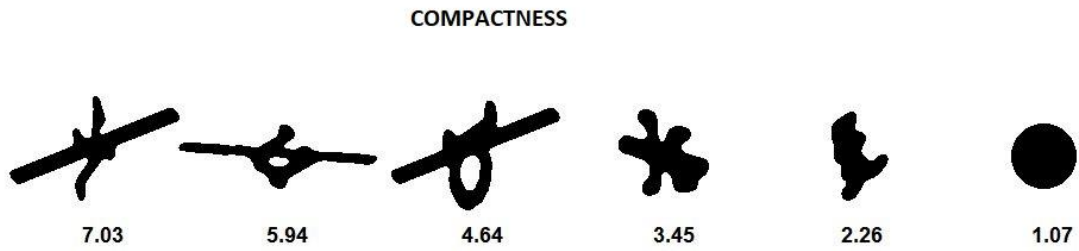
**Figure 18 - Bulkiness Example Diagram**

- **Bulkiness of the Fat**

A value for bulkiness of the region of fat is calculated for an input into the neural network. The region of fat is show above in Figure 17.

- **Compactness**

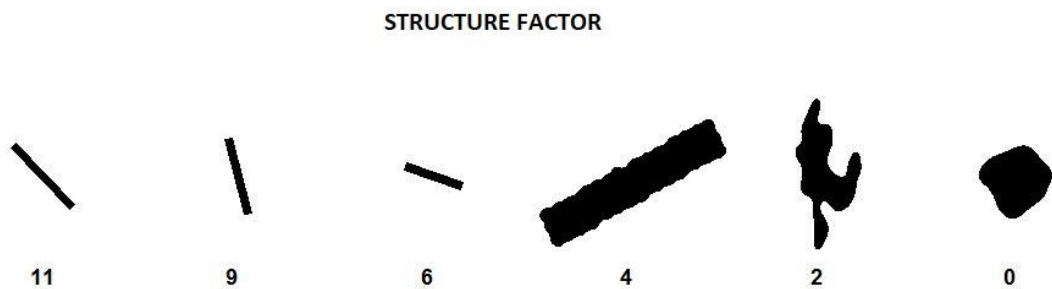
Compactness was used to gain a numerical value on how closely joined the area was of the whole primal cut region. Figure 19 illustrates different shapes and their compactness values.



**Figure 19 – Compactness Example Diagram**

- **Structure Factor**

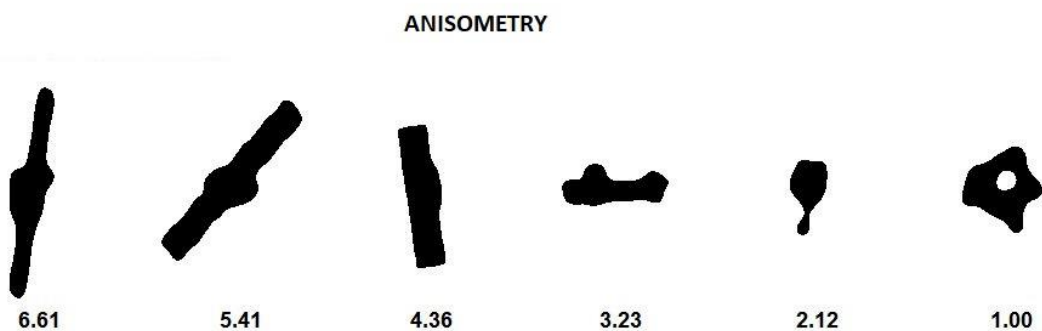
Structure Factor is another calculated shape feature value, it is a measurement of how long and thin the shape is, Figure 20 shows example shapes with their structure values.



**Figure 20 - Structure Factor Example Diagram**

- **Anisometry**

Anisometry is a measurement of how unsymmetrical the region is, Figure 21 illustrates shapes and their Anisometry values.



**Figure 21 – Anisometry Example Diagram**

- **Weight**

A measurement of the primal cuts weight is taken as it passes across the check weigh conveyor, this occurs prior to the meat passing under the vision system camera.

#### 4.3.2.5 HALCON MLP Neural Network Training

For the MLP neural network to be able to determine the primal cut, the network was required to be trained with substantial amounts of data from known primal cuts. A database of captured images was collected in-house by running each primal cut through the image capturing system, with the primal cut orientated in several directions and with both sides facing up. This database was then used to teach the neural network with its features determined from the image processing algorithms and the known type of primal cut passed to the neural network.

To achieve satisfactory results, the neural network required the calibration of two variables; the Input Layer, and the number of Hidden Layers to use. The Input Layer required features that were consistent to each individual primal cut of the same cut, but also varied amongst all the other different primal cuts. The number of hidden layers significantly influenced the output result; a small number of hidden layers reduced the complexity of the neural network, whereas a network of many hidden layers increased the chance of overfitting the data. Overfitting causes the neural network to classify using unimportant feature data and reduces its ability to generalise upon the results. Though the process of trial and error it was determined that nine hidden layers performed best for this neural network configuration.

#### 4.3.2.6 Check Weight Module

The load cells outputs were combined in the amplifier to provide a linear 4-20 mA output. In this scenario, 4 mA represented no load, while 20 mA represented the maximum load of 200 kg. This output was connected to the analogue reader to pass it into the vision software interface.

The application module was developed to record a sample of 5000 readings over 0.5 seconds to obtain an average measurement over time and filter the signal to reduce noise. This reading was then converted to weight in kilograms through previous calibration, which was sent to HALCON and used as one of the MLP inputs to help identify the primal cut.

#### 4.3.2.7 Communication Module

To interface with the different hardware used in the system, a communication platform was developed to allow the different components to interface together. Using this module, communication between the computer application and the LED lights to allow control over the on/off status, current, and different lighting modes of the lights could be initiated over an Ethernet connection.

#### 4.3.2.8 User Interface Module

The visual output from the primal cut recognition software displayed the type of primal cut as recognised by the system, the weight, length, width, and area of the primal cut. Feedback was also provided to the operators with detail regarding the profile parameters, including values of the shape of the cut and the fat percentage (MLP inputs). A visual display of the primal cut, its region, and area of fat was also displayed as an overlay on the screen as can be seen in Figure 22.



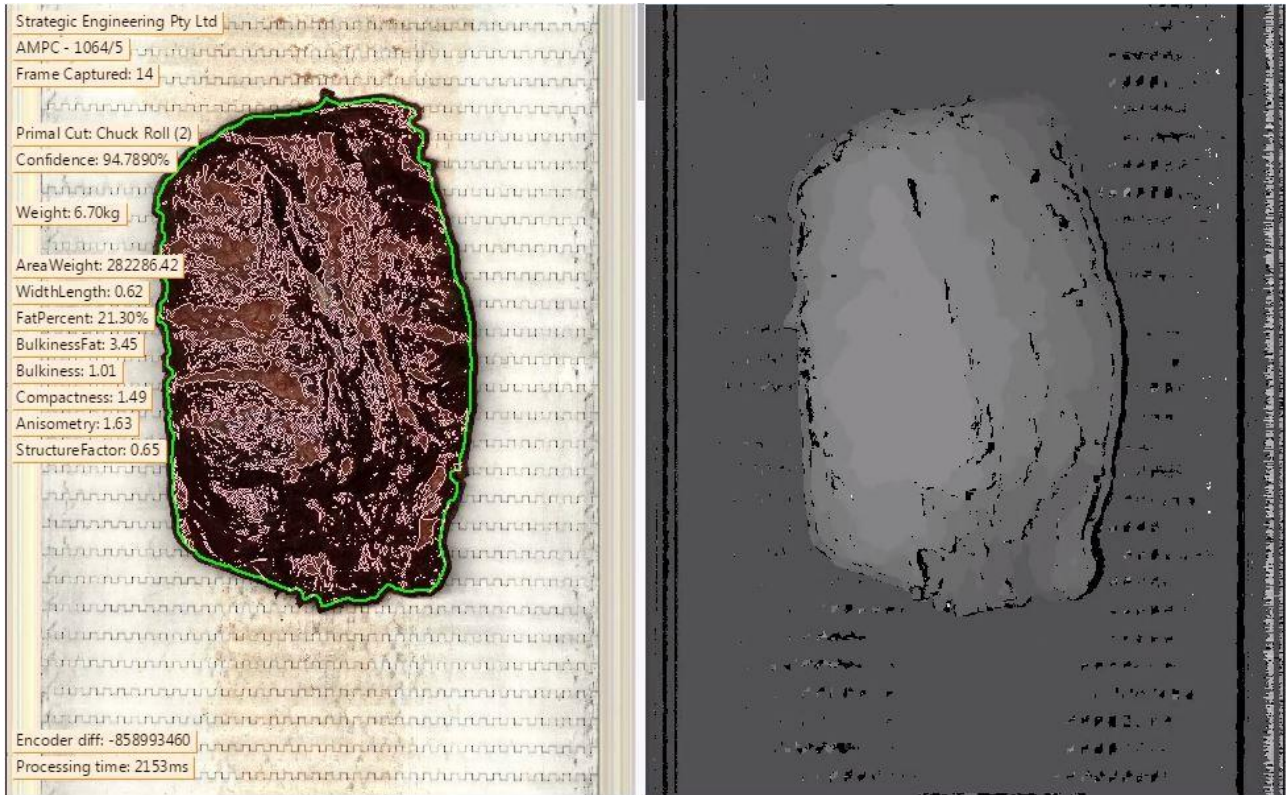
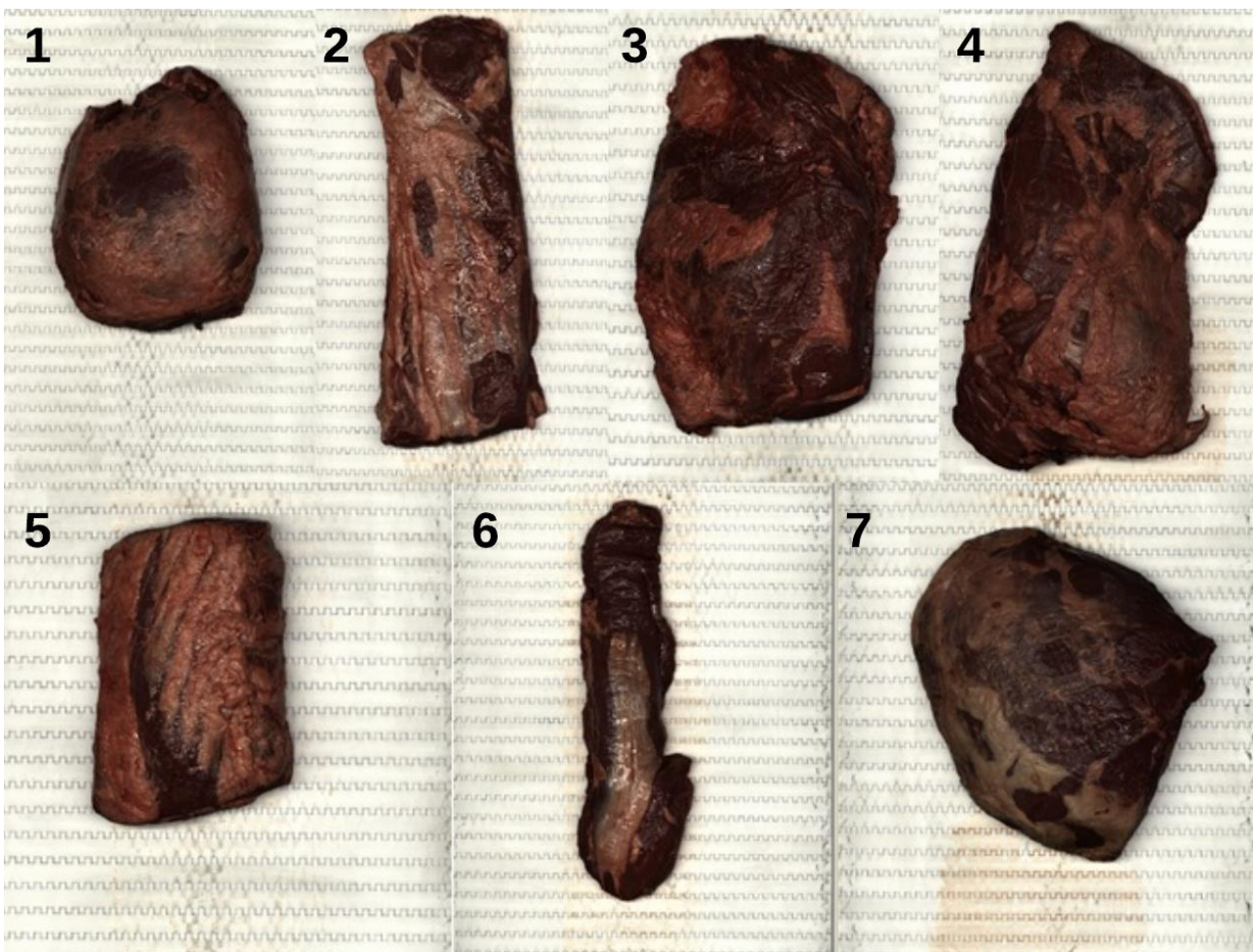


Figure 22: Software visual output

#### 4.4 In-house System Trials

For the in-house test the following primal cuts were trialed and are shown in Figure 23:

1. Knuckle
2. Striploin
3. Chuck Roll
4. Point End
5. Cube Roll
6. Tenderloin
7. Topside



**Figure 23: Primal cuts for identification trials**

Several different primal cuts were run through the vision system. Each cut was placed through multiple times in different orientations and alternating the side facing up. As the primal cut passed along the conveyor under the camera, the software would take the captured images and run these through the neural network to identify the primal cut. The identification was outputted to the screen where it could be validated by an operator that the system was working. The images captured during the trials were saved so they could later be run through the neural network for further validation testing. Figure 24 shows a primal cut travelling through the camera setup.





Figure 24: Trial set up



## 5.0 PROJECT OUTCOMES

The following lists the successful outcomes from this project:

- The development of a robust sensing network and software algorithms for rapid identification of a seven different red meat primal cuts.
- A software algorithm that could correctly identify a primal cut from image data, and produce a confidence level for operator observation. A low confidence would flag for an operator to confirm the cut and add that dataset to the neural network for continued growth and increased reliability of the system.
- An ability for the system to detect seven primal cuts, however, this could be expanded to cover an extensive range of primal cuts with limited modifications to the current system. Operators would only be required to add additional samples to be taught into the neural network. The addition of the extraction of additional features such as bone and contours from the images could also be readily implemented.
- Outputs three-dimensional data on each primal cut and several parameters via the graphical display to the operator.
- The hardware for the system was been developed to take up minimal space inside a red meat processing plant, with the camera mounted overhead of the conveyor to reduce floor space requirements.

## **6.0 DISCUSSION**

### **6.1 Neural Network Training**

For a neural network to reach a high level of accuracy, the network is required to be trained using a large database of sample images. For in-house testing, the system was trained with approximately seven of each primal cut. The primal cuts were placed under the vision system facing each way up and rotated to numerous directions to be able to build up a large database of training images.

Integration into a commercial plant would require the system to be run for a period to gather a significantly larger sample size of classified images. To gather this data, the system would operate continuously, as each primal cut passed under the system an operator would be prompted to identify the primal cut to assist with identifying images for the MLP neural network. This could be set up with a simple HMI interface for the operator to see an image of the last cut through the system, and select the primal cut from a predefined list of cuts.

### **6.2 Neural Network Performance**

From testing conducted in-house, the neural network performed perfectly across each tested primal cut. Each previously unseen and untaught primal cut that was passed through the vision recognition system was correctly identified with a confidence above 90%. If an object or other primal cut that was not part of the trained list of cuts passed through the system, a confidence of under 65% was reported. When integrated with a plant, this confidence feature could be used to flag unknown primal cuts or other foreign objects that have fallen onto the conveyor to an operator.

### **6.3 Integration**

The overall system was designed to be versatile and easy to integrate into a commercial plant's production line. The frame holding the vision camera above the conveyor was minimal in size and could fit into tight space constraints. The vision control cabinet could be located anywhere within ten meters of the camera, allowing for flexibility of the cabinet location. The only other requirement for integration was to attach an encoder onto the plant's existing conveyor motors to allow the line camera to capture images correctly.

### **6.4 Process Time**

The average processing time from capture of the image to the identification of the primal cut was 1.5 seconds. This processing time is sufficient, as the primal cuts would be tracked along the conveyor into a packing and labelling system allowing for additional processing time if required by the vision system. The primal cut identification would be passed to the labelling system along with the weight and any other details required for labelling. It would be possible to increase this processing speed with additional hardware if required for a plant installation.

## 7.0 CONCLUSIONS/RECOMMENDATIONS

Overall, the development of the Naked Primal Cut Recognition Software was successful. The system was able to correctly identify seven different primal cuts, and provide feedback to the operators of the profile parameters. This project has set the framework required for a system to be integrated into a plant, with the ability to reduce the requirement of skilled labour that is currently used for primal cut identification. The system has the ability to integrate within an automated plant and communicate with an inline bagging and labelling system.

### 7.1 Suggested Next Step Points of Action

- Recommended that the system is set up within a plant environment to develop a larger set of primal cut data and to trial the system's full capabilities.
- Increase the range and size envelope of primal cuts that the system is able to recognise.
- Further develop the system to allow for identification of primal cut characteristics such as marbling and colour to potentially allow for automated grading.

Additional input features could be added to the system to aid in primal cut identification as required. The end result for the system is to increase the range of primal cuts to the plant processors entire product range, and to completely automated the identification, grading, and labelling of these primal cuts, while significantly reducing skilled labour requirements.

## 8.0 REFERENCES

MVTec. (2017). *HALCON Operator Reference 13.0.1*. Retrieved from Halcon:  
[http://www.mvtec.com/doc/halcon/13/en/toc\\_regions\\_features.html](http://www.mvtec.com/doc/halcon/13/en/toc_regions_features.html)

## 9.0 APPENDICES

### 9.1 Vision PC Components

**Table 4: Off the shelf computer components for vision system**

Image	Component Name	Part
	Intel Core i7 6900k	CPU
	MSI X99A Gaming Pro Carbon RGB Motherboard	Mainboard
	NVIDIA TITAN Xp 12GB	GPU
	Corsair Vengeance LPX CMK16GX4M2B3200C16 16	RAM
	Samsung 850 EVO 1TB SSD	Disk Storage
	Corsair HX1200i 1200W 80 Plus Platinum Power Supply	Power Supply

	<p>Noctua NH-D15 CPU Cooler</p>	<p>CPU Cooler</p>
	<p>Corsair Carbide 270R ATX Mid-Tower Case</p>	<p>PC Enclosure</p>
	<p>Bitflow Dual Camera Frame Grabber; AXN-PC2-CL-2xE</p>	<p>Expansion Card</p>
	<p>Digilent Analog Discovery, Multi-functional Analog and Digital Instrument</p>	<p>USB Device</p>



**Table 5: Sensory and transportation hardware for the conveyor system**

Image	Component Name	Part
	Bongshin DBBP series S Type Load Cell 50kg	Load Cell
	SICK Incremental Encoder DFS60 10,000 PPR	Encoder
	SICK Photoelectric Sensor W12G	Sensor
	UNI S-MPB PP Modular White Belting	Conveyor Belt
	SEW WA37/T 0.37kW Spiroplan Gearmotor	Gear motor