Intelligent solutions for boxed beef trim export enhancement

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TABLE OF CONTENTS

TABLE OF CONTENTS 2
1. EXECUTIVE SUMMARY 4
2. INTRODUCTION 6
3. PROJECT OBJECTIVES 6
4. METHODOLOGY 6
5. PROJECT OUTCOMES 7
6. DISCUSSION 7
7. CONCLUSIONS/RECOMMENDATIONS 8
8. Bibliography 10
9. Appendix 1- Development of a prototype for automated box inspection and documentation and a report of its performance benchmark 12
9.1. Introduction 12
9.2. International adoptions of vision technology 12
9.3. Assisted automation 13
9.3.1. Beef primal cuts 14
9.4. Method 16
9.4.1. Feature recognition method 16
9.4.2. ‘Convolutional Neural Network’ (CNN) 17
9.5. Software development 18
9.5.1. Transfer learning Google Inception V3 18
9.5.2. Basic description of the software 19
9.5.3. Flow of information and controls: 19
9.5.4. Android application 20
9.5.5. Arduino code 21
9.6. Conceptual and prototype apparatuses 22
9.6.1. Conceptual test bed 22
9.6.2. Prototype test bed 22
9.7. Experiments 28
9.8. Network training 29
9.8.1. Project’s GPU server 29

9.9. Final lab test and demonstration 31
9.10. Future improvements 32
10. Appendix 2- A feasibility report of the integration of the box inspection data in an overall slaughterhouse operation 33
10.1. Implementation/integration: cost-cutting measures for more profit 33
10.1.1. MHS 34
10.1.2. Enterprise Resource Planning (ERP) 34
10.2. Costs & benefits of a "total system" implementation and TCO 34
10.3. What influences the TCO? 35
10.3.1. Implementation 36
10.3.2. ERP costs vs time 37
10.3.3. Application licensing 38
10.3.4. Database, OS and identity management 38
10.3.5. Computing hardware 39
10.3.6. Implementation services 39
10.3.7. Internal human resource costs 39
10.3.8. Ongoing maintenance 40
10.3.9. Hidden costs 40
10.4. Benefits of the total system 41
10.4.1. Benefits 41
10.4.2. Integrated financials 42
10.4.3. Integrated orders 42
10.5. Faster processes 42
10.5.1. Reduced inventory 43
10.5.2. Other benefits 44

1. EXECUTIVE SUMMARY

With the growth of the beef industry in Australia, speed of operations in slaughterhouse lines has dramatically increased. Grading of slaughtered beef cattle is subjective, inconsistent, inaccurate, and slow. Also, the wide variations in beef cattle genetics complicates the classification of beef cuts, products and quality data documentations. This can eventually result in mislabelling. To address these challenges, intelligent automation is considered as a viable solution for fast, objective, consistent, and accurate beef grading of quality and yield grades of beef carcasses and labelling of the beef cuts.

Intelligent automation (Industry 4.0) for complex shop-floor processes in the meat industry offers significant potentials, starting with the reception of livestock. When animals arrive, all relevant data should be entered electronically so they can be supplied to cutting, production, packaging and inventory without any media disruptions. This increases information quality and transparency in the entire operation, while errors and costs can be reduced substantially. In most cases, investments in IT-aided goods receiving, be it stationary or mobile systems, are quite manageable as existing intelligent automation can be integrated and available hardware can be used.

Current packaging and labelling of the product does not provide the needed checks on quality and box integrity for the exported "boxed beef trims". Intelligent automation and digitisation have the potential for higher processing speed and thus less waste (and more freshness) in the meat industry. This is due to increased transparency and efficiency, full traceability, control of complexity which typically results from the intelligent automation.

In this project, national and international common practices in grading, carcass identification and its tractability were studied and those that can contribute to the quality and integrity of packaging in Australia were outlined, analysed and assessed.

In our first milestone report, market requirements for Australian beef export and their parameters were studied and ways of improving the export was outlined. Also, national and international existing practices on beef carcass and beef cut identification, tractability, packaging, integrity checks and their documentation were reviewed. Parameters of beef export that can potentially impact the export were also discussed.

Solutions to rectify the mislabelling issue based on the existing technologies available to AMPC were presented as the second milestone report for this research and their feasibilities were analysed and discussed. The history and details of the technologies available to AMPC and other useful technologies were examined. Problems with packaging, integrity checks and documentations were identified. Furthermore, a parametric cost-benefit model was developed and utilised to analyse the issues with package integrity checks and documentations in Australian abattoirs.

A state of the art automated inspection system using the Deep Artificial Neural Network technology, for the "assisted automation" of beef cut labelling recognition has also been developed. The final system was implemented on a mobile phone, which conveniently integrates the camera, touch display and the required computing power. In this system, the vision system views the boxed trims and presents the operator with a likely choice for its label. The operator can then choose from suggested classification options provided by the program and confirm it before a label is printed and affixed to the box.

This research provides a set of best practices including adoption of machine vision automation technology to rectify the current issues with mislabelling, package integrity checks and documentation in Australian abattoirs. This would eventually allow to achieve measurable success in practice equally suitable for small and for large-scale slaughterhouse operations.

The following recommendations are based on the findings of this research:

A need for national requirements on document control,

A need for increased intelligent automation I4.0, technology integration and automation,

Need for development of total system for the use of I4.0 technologies.

2. INTRODUCTION

Computer vision technology uses image processing and data analysis to enable machines to recognize objects and extract quantitative information from digital images. These capabilities can be effectively utilised for evaluation and monitoring of product quality in manufacturing industries in an objective, rapid, non-contact, and non-destructive fashion.

Recent proliferation of computationally powerful processing hardware with large memories and affordable prices has led to many computer vision-based solutions implemented for a wide range of product quality control applications. Particularly, in recent years, the technology has been employed by a number of food product manufacturers for quality evaluation of their products and processes.

Thanks to the rapid scientific and technological advances in computer vision, it is increasingly becoming the preferred technology for quality inspection, classification, and evaluation of a wide range of products in the food and agricultural industry such as meat supply chain.

This project aims to study the current labelling practices for boxed beef trim exports and integrity inspection/documentation at different Australian abattoirs. Also, the project investigates the feasibility of using the technologies available to AMPC to rectify mislabelling issues and integrity checks and documentation. A prototype for a system is built and demonstrated to rectify the mislabelling, integrity check and documentation for the beef export industry using machine vision technologies based on Deep Artificial Neural Networks.

3. PROJECT OBJECTIVES

The following objectives have been agreed for the current research project:

- Investigate the extent and causes of the mislabelling problem
- Study the issue of market complexity for boxed beef export
- Identify possible solutions for the rectification of the mislabelling problem
- Identify ways of simplifying the labelling processes via finding and separating common requirements
- Find pathways for the adoption of AMPC-owned technologies for the full automation of the labelling process
- Investigate the potential benefits of box integrity documentation
- Devise a plan and conduct a feasibility study for the adoption of AMPC-owned technologies for the full automation of the labelling process

4. METHODOLOGY

Several visits have been made to a number of abattoirs in Queensland and Victoria to meet people in charge of the quality systems, processing and packaging. This enabled to study the current practices in meet cut identification, labelling and their integrity checks and documentation system. The review identified processes or practices that might have the potential to cause mislabelling issues. Also, a large number of relevant literature including ~170 technical reports, articles, legislations/regulations and books were studied. These were carefully considered for their similarities in technologies, systems and procedures and were compared with those which are common in Australia.

Classical design methods were adopted in this project for its experimental and technology demonstration parts. This included to undertake the following steps for the designs: conceptual design, construction, test, design review, detail design, embodiment, manufacturing and commissioning.

5. PROJECT OUTCOMES

We performed a comprehensive review of market requirements for important export markets with the view of identifying the common requirements.

We identified some of the best possible combinations of technologies for rectification of mislabelling problem. The emphasis was on finding pathways for commercialisation of the AMPC-owned technologies.

During this research, appropriate measures are suggested to quantify the success of the labelling issue so that a plant performance can be both measured and benchmarked. The measures are also verified and compared with the industry best practices to ensure that the proposed solution meets the overall industry requirements.

A parametric model of the cost benefit analysis for the box integrity inspection and documentation was developed and conducted.

Existing technologies available to AMPC and some other useful technologies were reviewed. The possibility of adopting these “off the shelf technologies” to automate the labelling, inspect integrity of boxed beef trims packaging and their documentation was discussed.

Two test beds (conceptual and detailed prototype) have been designed, constructed and tested. Software including in-house customised and commercial were developed and utilised. A GPU server was acquired and utilised for network training of the Deep ANN solution. Large databases of different cuts of meats were constructed and employed for network training of the automated recognition systems. A prototype for automated box inspection and labelling, on a mobile phone, was developed and tested. The performance of the developed system was carefully measured and reported. A feasibility report of the integration of the box inspection data in an overall slaughterhouse operation was also prepared.

6. DISCUSSION

First of all, the cost benefit analysis presented as part of this project only included the mislabelling costs. The benefits were limited to considerations of the rejection of the pallets and fixing the errors in the abattoirs. It is important to note that this is not always the case. Recently, the mislabelling issue resulted in a temporary ban on Australian beef export by China (Doran and Dziedzic, 2017) with unknown cost to industry. In the second milestone report of the current project, a detailed cost-benefit model was modelled and performed. The model presented a quantitative estimate for costs and benefits relevant to a vision-based labelling, box integrity inspection and documentation.

Secondly, the integration of the box inspection data in an overall slaughterhouse operation is a broader issue compared to a simple cost benefit analysis. The integration involves an inclusion of the proposed intelligent technology in this research into a comprehensive (total) system. This requires major changes in all levels of the system which eventually incurs several costs to the entire industry. A feasibility analysis at this level should consider under the broader banner of “Total Cost of Ownership” (TCO).

7. CONCLUSIONS/RECOMMENDATIONS

As demonstrated in the first milestone report, some key market requirements for the beef export in Australia are correlated with parameters of its production, supply chain and consumption. The predictive models (e.g. (Silva and Gurría)) can be used to estimate the trend of meat production, consumption and growth in Australia.

Backed by several site visits and interviews of current practices in Australia and other international beef exporters, key technologies for an automated labelling and packaging integrity inspection and documentation were analysed.

Adoption of proper technologies, such as machine vision solutions, can rectify the mislabelling, package integrity checks and documentation issue.

Our recommendations on implementation of the technologies to the boxed beef trims industry can be summarised as:

- Mislabelling, integrity checks and documentation can be improved using new labelling technologies such as QR-code, "Reduced Space Symbology (RSS)" and "Radio Frequency Identification (RFID) tags" technologies.
- Intelligent packaging, as discussed in this report, may be considered as a solution for both labelling, packaging and documentation. Both RSS and RFID tags technologies offer a more efficient tracking (without introducing errors) and a more streamlined documentation. A vision-based cut recognition and localisation software requires the code to be affixed to each cut for its identification.
- From a packaging and processing perspective, affixing a label onto every primal cut is required to allow an automated processing, tracking and documentation system. However, it adds an additional unit of manual labour.
- The parametric model of cost benefit analysis for adoption of an integrity check and documentation solution showed that in less than a year, the costs for the machine vision technology can be recovered.

Based on the cost benefit modelling and analysis developed by the authors, this is quite feasible and the economic savings of an "integrity check and documentation solution" offsets the costs. It would also be beneficial to (semi)automatically identify and attach the label required for the solution. Recent ongoing developments and progresses in camera sensor and image perception technologies have made solutions such as those stated in this report more feasible than before in the beef export industry. In particular, the use of Convolutional Neural Networks has provided an affordable and robust technological approach to automated visual inspection and optimisation of labelling, integrity check and their corresponding documentation.

The suggested technologies, reviewed and analysed in this report, are essential to develop a naked primal cuts recognition software system. The vision-based technology enables identification and placement of the primal cuts in the appropriate sized bag, sealed and affixed with either of the recommended codes/labels.

Machine vision for identification of cuts of beef will be specifically useful for tracking and identifying various beef portions, without the use of physical tags and barcodes attached directly to the meat or to the container holding them. This removes the possibility of foreign bodies entering the food or tags being lost within the product. This also removes the risk of boxes being lost track of their origin because tags where swapped or removed or incorrectly affixed in the first place.

The results achieved from this project are promising. To get such high accuracy results in the both the trained network testing and the real world experimental setup is a significant proof of concept. Even though the results were successful, the tests performed as outlined in this report had some limitations and the potential for improvement exists, this fact really speaks to the power of deep learning and artificial intelligence and the potential benefits of its implementation in this industry.

Future plans for this work include:

- Increase the size of the database of images the network is trained on – it is generally recommended a minimum of 1000 photos for each class that has to be classified. This project used 1000 split between 6 different classes, due to the limited access to images. Increasing this to the recommended 1000 images per, class, a 600% increase, would drastically increase the accuracy and reliability of the networks classifications.
- Improve the real-world test setup to give a more accurate representation of what would occur in real conditions:

Final real-world testing gave results between 87.5% and 99% accuracy, and as mentioned above, these can and will be improved with suggested future alterations. This project and experiment has been a success and proves the reliability, and potential accuracy of implementing such a system into the meat industry.

Integration of the technology requires a total system. To implement the new technologies in a total system has to be seen from a broader perspective and the “total cost of the ownership” (TCO) for the implementation has to be considered.

Some of the key considerations for TCO was discussed and reviewed in Appendix 2 of this final report.

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9. APPENDIX 1- DEVELOPMENT OF A PROTOTYPE FOR AUTOMATED BOX INSPECTION AND DOCUMENTATION AND A REPORT OF ITS PERFORMANCE BENCHMARK

9.1. Introduction

To survive in the current competitive meat industry, automation is an inevitable necessity. Manual handling of offers, orders, purchase orders, invoices or delivery notes are very slow and prone to errors. Lacking proper communication between the different departments results in some data being processed several times which in turn increases processing time and risk of errors.

While the mislabelling of beef products has been an international issue (Earl and Porter, 1992) which also requires international legislation and standardisation (Summers and Campbell, 2008), this report deals with common practices of labelling in Australian abattoirs and mislabelling arising from human errors, technical issues, integrity checks and lack of quality documentation.

For the sake of completeness, a brief summary of international adoption of vision technology to solve similar problems will be presented next.

9.2. International adoptions of vision technology

One of the early applications of the vision technology for meat cuts is by Tan et al. who applied the technique for assessment of fresh pork colour with colour machine vision techniques (Tan et al., 2000).

Tenderness classification was carried out by Weeler et al. They compared efficacy of three objective systems for identifying beef cuts (Wheeler et al., 2002). They examined the accuracy of 3 objective systems (prototype BeefCam, colorimeter, and slice shear force) to identify guaranteed tender beef.

Another research and technology demonstration was carried out by Brosnan and Sun who discussed application of machine vision using both statistical and neural network models (Brosnan and Sun, 2002). They found that the neural network models to be most accurate; a prediction error of less than 0.6 was produced for 93 percent of the 44 examined samples.

Song et al. employed ultrasound to measure back fat thickness, longissimus muscle and intramuscular fat before slaughter (Song et al., 2002). They concluded that an improved system is needed for accurate and rapid measurements of yield grade and quality grade in live cattle.

A summary of characterisation of quality attributes such as colour, marbling, maturity and texture; prediction of sensory scores and grades; and prediction of cooked-meat tenderness was presented by Tan et al. (Tan, 2004). They demonstrated the promise of computer vision for objective meat quality evaluation and discussed the remaining challenges. They demonstrated prediction of USDA beef quality and yield grades from image features. They discussed that the conventional quality indicators such as colour, marbling and maturity could be misleading as they overlook important quality measures such as tenderness.

A PhD thesis was sponsored by Danish Meat Research Institute (Larsen, 2016). Larsen studied learned image representations for visual recognition. The thesis explored two approaches to constructing image representations, namely feature engineering and feature learning.

Zheng et al. used computer vision technology extensively for food quality evaluation (Zheng et al., 2008) including Quality evaluation of meat cuts.

Prevolnik et al. summarised application of Artificial Neural Networks in meat production and technology (Prevolnik et al., 2011).

A relatively recent demonstration of the vision technology is that by Larsen et al. (Larsen et al., 2014). They used the technology to avoid issues associated with mislabelling and tractability of Meat cuts. They dealt with meat traceability from farmer to process and quality parameters during packing and dispatch. They showed that the machine vision technology can handle perturbations such as hanging, rough treatment and incorrect trimming relatively accurately. They demonstrated the use of visual recognition technology for meat cut identification which included segmentation, canonization, description and matching.

Ludwiczak et al. used ultrasonic images processing and analysis in Polish meat industry (Ludwiczak et al., 2015). This included different methods of image segmentation in the process of meat marbling evaluation.

Density of lean meat tissue in pork was measured using computed tomography (CT) by Hiviid (Hviid and Vester-Christensen). They also measured distribution of density in the pork carcass.

9.3. Assisted automation

Given the critical nature of mislabelling issues and the learning based nature of Artificial Neural Network (ANN), a reasonable *transition* between the existing fully manned labelling processes and those of a fully automated labelling is essential. This transitional stage is called "assisted automation".

The assisted automation requires an existing manual labelling system and the classification capabilities of ANN is offered as an option to the operator to choose from.

As an example of the existing manual system, a tracking system algorithm (Mousavi et al., 2002) is considered here (see Figure 1). (Mousavi et al., 2002) discussed developments in tools and techniques to improve the production process in handling and cutting meat portions for end users. They suggested to employ existing "material handling systems" (MHS) and their software/hardware, logistics and technical requirements for tracking meat cuts in a production process. They proposed to employ such established tools and techniques as a practical solution for the development of a tracking and traceability system within the meat industry. They demonstrated a customised version of the system which was capable of identifying and handling a product and the information attached to meat cuts throughout the production process to retail packs.

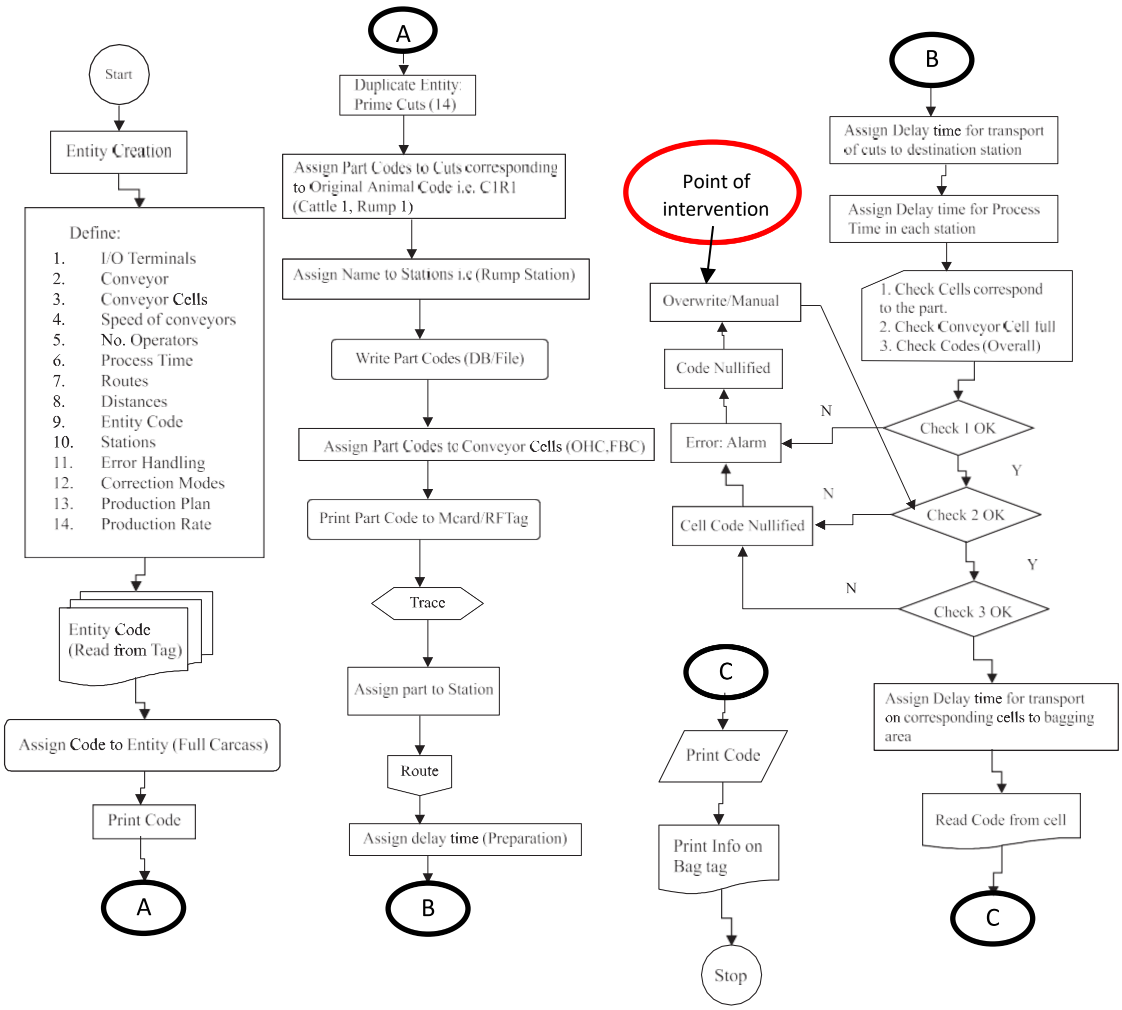


Figure 1. A typical label check (Mousavi et al., 2002) and its suggested point of intervention for an assisted automation

9.3.1. Beef primal cuts

Australian abattoirs have divided the carcass into 8 sections (primal cuts) (Hardecke, 2018). These include Rib, Loin, Chuck, Sirloin, Round, Shank, Brisket, Plate, and Flank. These are divided in turn in sub primal cuts. Meat and Livestock Australia (MLA) classifies the beef primal and sub-primal cuts and their weight ranges are as shown in Figure 2 and Figure 3, respectively.

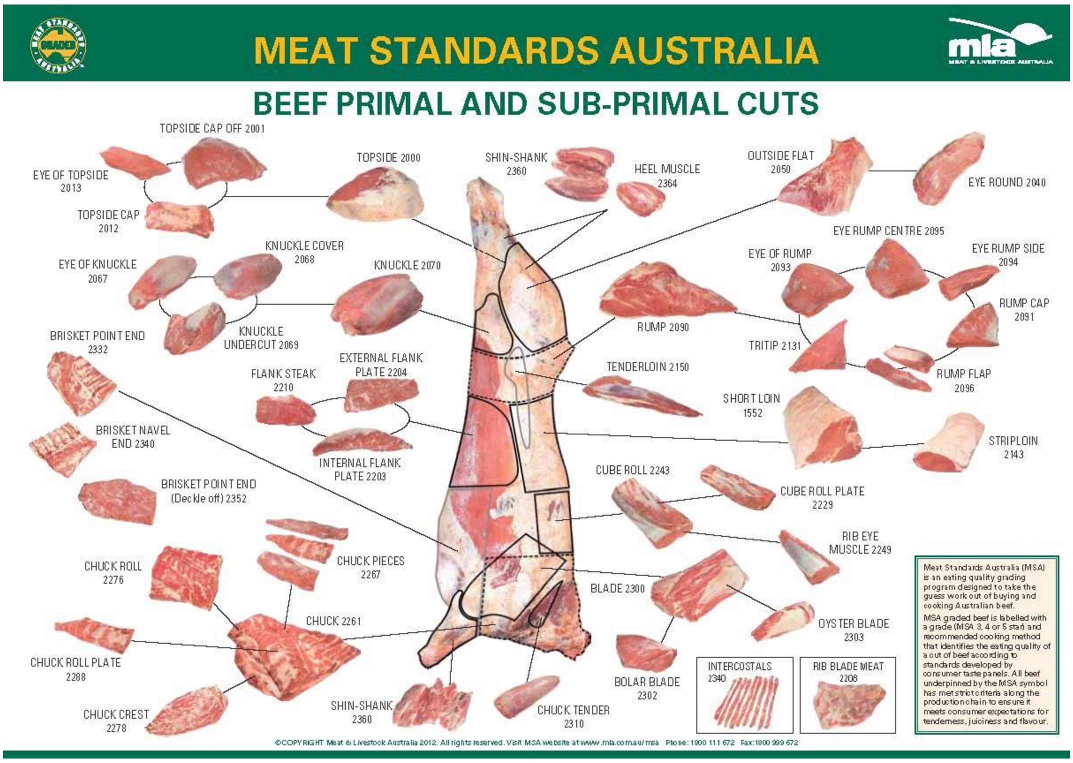


Figure 2. MLA’s classification of primal and sub-primal cuts

This primal cut weight range guide is used to calculate the average weight of meat primal from various carcase weight ranges. It is a helpful tool when selecting a primal for portion cutting or roasting.

PRIMAL								
CUT		Striploin (3 rib)	Tenderloin	Cube Roll (5 rib)	Cube Roll (8 rib)	Blade	Chuck Roll (5 rib)	Chuck Tender
* H.A.M. NO.		2140	2150	2240	2244	2300	2275	2310
CARCASE - PRIMAL CUT WEIGHT RANGES	carcase %	4.4	1.6	1.7	2.8	5.5	4.8	0.9
	160-180kg	3.5 - 4.0	1.3 - 1.4	1.4 - 1.5	2.2 - 2.5	4.4 - 5.0	3.8 - 4.3	0.75 - 0.80
	180-220kg	4.0 - 4.8	1.4 - 1.8	1.5 - 1.9	2.5 - 3.1	5.0 - 6.0	4.3 - 5.3	0.80 - 1.0
	220-260kg	4.8 - 5.7	1.8 - 2.1	1.9 - 2.2	3.1 - 3.6	6.0 - 7.2	5.3 - 6.2	1.0 - 1.2
	260-300kg	5.7 - 6.6	2.1 - 2.4	2.2 - 2.6	3.6 - 4.2	7.2 - 8.3	6.2 - 7.2	1.2 - 1.4

This information is to be used as a ***GUIDE ONLY.***
** H.A.M. - Handbook of Australian Meat Reference Cut Item and Code Number.*

GUIDE TO CARCASE BODY YIELD

- *PRIMAL CUTS ACCOUNT FOR : 60%*
- *TRIMMINGS : 10%*
- *BONE : 20%*
- *FAT : 10%*

TOTAL : 100%

** These percentages are a* ***Guide Only*** *to a carcase body yield.*

Figure 3. Primal cut weight range guide

9.4. Method

Artificial Neural Network (ANN) is the chosen technique for classification in this project. This classification technique is a "computer vision-based" method which has been widely used for food quality evaluation. Its aim is to replace the human visual decision-making process with automatic procedures.

In this project, the technique identifies primal cuts by classifying them into one of the finite sets of classes. This involves comparing the measured features of a cut with those of a known cut or other known criteria and determining whether the new cut belongs to a particular category of the primal cuts. Typically, the classification relies on the images of the cuts that are quantitatively characterised by a set of features, such as size, shape, marble, colour, skeletal maturity, tenderness and texture. These are also used to form the training sets.

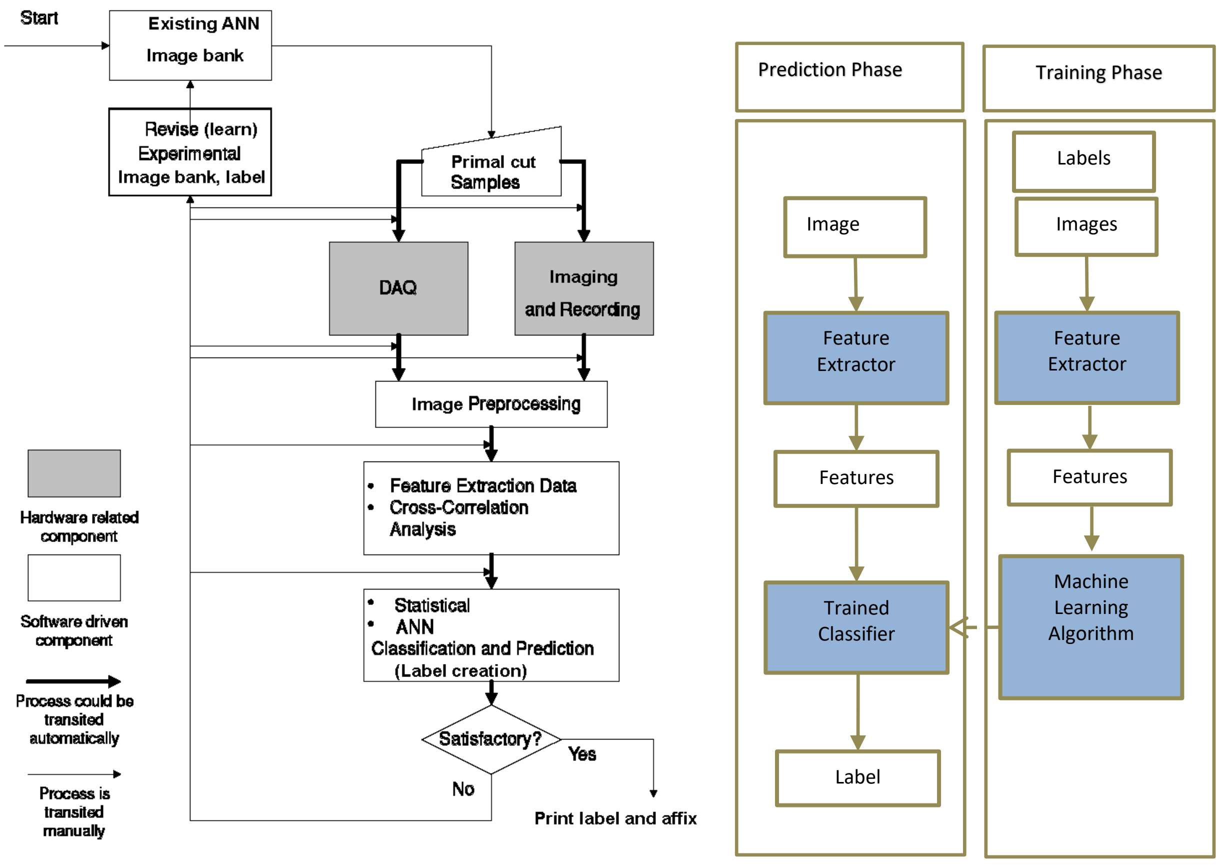
9.4.1. Feature recognition method

To identify the beef primal cut features correctly, the following four steps (Larsen et al., 2014) are considered:

1. Segmentation: First, the cut is segmented. That is, the primal is cut out from the background image pixels. Sample segmentation tools are Binary, Deriche, Hessian and Canny filters (Ludwiczak et al., 2015).
2. Canonization: The segmented primal cut images are then brought to a canonized form to minimise variability from external sources, e.g. illumination.
3. Description: A description of the image structure is generated from the canonized images
4. Matching: Finally, the primal matching is performed by comparing the descriptors from the previous stages.

Using these knowledge, intelligent decisions (outputs) are made first and then based on the feedback to the knowledge base, classifiers are induced. A classifier identifies a simple yes or no answer or an estimate of the probability that a cut belongs to each of the primal cuts (candidate classes).

The basics of the ANN prediction and training are shown in Figure 4.



Structure of assisted automation for label selection and printing. **Machine learning phases**

Figure 4. Left: Assisted automation to identify a label (ANN-based) and Right: ANN-based learning and label producing.

Network training is a "computationally extensive" step which is carried out by a GPU server. After completing the training, weighting factors are sent to the image processing devices that identify the classifications and issue the labels. The latter will be carried out using a mobile device and will be explained later in this appendix.

9.4.2. 'Convolutional Neural Network' (CNN)

'Convolutional Neural Network' (CNN) has been commonly used for image recognition applications such as ImageNet, a large scale worldwide image recognition undertaking. CNN is used throughout this project for deep learning as the best implementation method.

To develop the needed image recognition software for the current prototype test bed using the deep learning and CNN applications, MATLAB software was chosen as the development environment.

Preliminary development included integration of CNN within MATLAB on how to use transfer learning to re-train a network. Training a CNN from scratch that could handle this project's database (beef images) would have been very time consuming and much more technically involved. As an easier access path into the world of CNN's, an existing pre-trained CNN was chosen. Then the pre-trained CNN was trained further using a database of beef cut images. This saved time in the initial creation and training of the network. This method is commonly used in the field and is known as '*transfer learning*'.

This method is popular because it is often difficult to acquire a large enough data sample to train a given network from scratch. To train a network on the largest dataset available, ImageNet, which has over 1.2 million images in 1000 categories, enables the network to learn basic features like edges and colour segment information that will be of use in many applications. The early layers of such a network learn the vague outlines and edges and colours and can be applied to many different cases. Only in the later layers of the network will the specifics of the given images be used to finalise the recognition. These are the layers that are 'fine-tuned' to the given intended data set.

The pre-trained network which was utilised and implemented at "the conceptual stage" of this project (conceptual test bed) in the conceptual design stage is AlexNet CNN. The network was trained on the massive global image database accumulated, called ImageNet. In the prototyping stage, Google Inception V3 network was used, which was trained on the same ImageNet database.

Although implementing transfer learning allows one to effectively pick up where another data set has left off, it still requires a large number of images to be able to perform the given specific task and to deliver a final result with some desirable degree of accuracy. It is a known fact that typically, about 1000 images are required, per class to categorise an input image accurately. This is understandably difficult and demanding from database collection perspective, especially for such a specialised item as primal cuts of beef.

As far as technology demonstration for this project is concerned, it is essential to choose enough example cuts to test the practicality and feasibility of the technology to justify its expansion as an option.

9.5. Software development

A software was developed for the automation of labelling. During several stages of the project, different computer codes were developed to suit different platforms/OS's. Eventually, at the final stage of the project, the software was ported to an Android mobile for the technology demonstration prototype. These were accomplished using Arduino Integrated Development Environment (IDE). To train the network "Python programming language" and "tensorflow open-source software library" were used.

9.5.1. Transfer learning Google Inception V3

The CNN used at the "detailed design stage of the project" (prototype test bed) to transfer learn in the prototype stage is Google Inception V3, which is trained on ImageNet database. The CNN has been used in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). It is originally trained to classify 1000 classes. We retrained the CNN using transfer learning technique to classify six classes of meat. Specifically, first we retrained the top layer, which is known as the bottleneck layer. This layer receives 2048-dimensional vector. Then, on top of this vector representation, a softmax layer was trained to classify the six classes. This is equivalent to learning 6 + 2048*6 model parameters which are comprised of biases and weights.

The retraining was performed in Python programming language using TensorFlow open-source software library on a NVIDEA GPU server. Spyder open-source IDE was used to manage the programming. After performing the transfer learning, the retrained network was performed with a validation accuracy of 96%.

The trained network was then optimised to be used in a mobile application, as a larger network needs more computation time. This was achieved by stripping off unused portions of the network.

Furthermore, this operation makes sure that the network can be compressed. In this instance, the retrained network had a size of around 95MB which was later compressed to a size around 55MB.

The optimised network was then used in the Android application which performs in the following manner.

9.5.2. Basic description of the software

The repository used for the software contains two folders, one for the Arduino code and another for the Android code. In the Android folder, there are two folders where the source files for two applications are stored. One is to control the conveyor belt (using the inbuilt WiFi connection of the Arduino compatible Wemos D2 R1 with ESP8266 module), and the other is just to test the trained network. One can train their own network, freeze the model in *tensorflow*, quantise and optimise it for mobile use and include it in the assets folder for this Android project.

9.5.3. Flow of information and controls:

A flowchart showing interaction and controls of different modules for the software is shown in Figure 5.

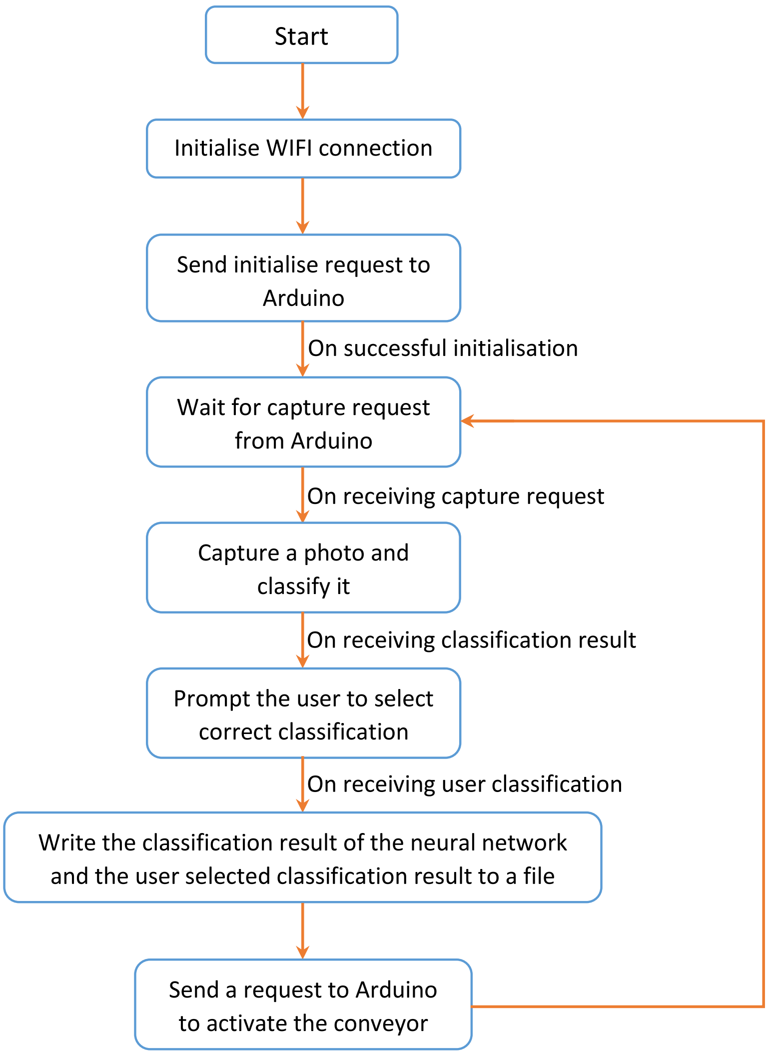


Figure 5. High level flow chart of the Android application

The flowchart in Figure 5 shows the "assisted automation" for labelling in which the operator is presented with a list. The operator can choose from suggested classification options provided by the program and confirm it before printing and affixing to the box.

A sample components/modules of the high level program is "conveyor control" routine which is shown in Figure 6; it sets up the; conveyor controller application.

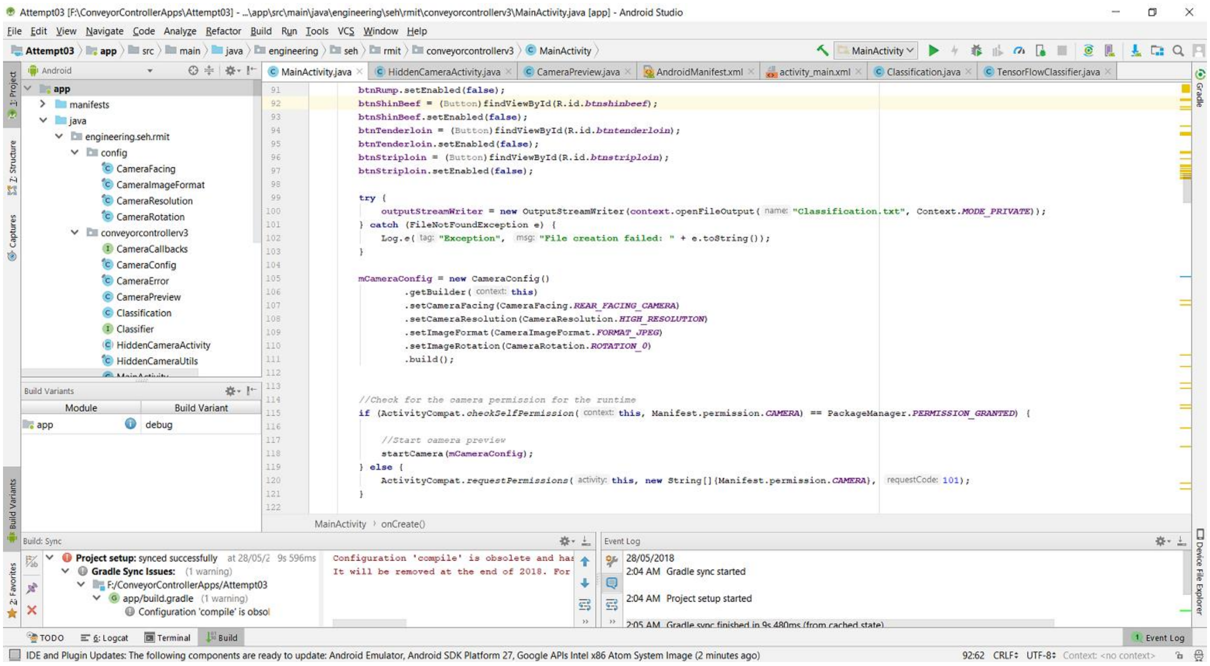


Figure 6. Android Studio "Integrated Development Environment" (IDE); typical components for conveyor control software

9.5.4. Android application

The developed Android application is an event driven program which performs appropriate actions for various events including the followings.

On Create:

- Initialise WiFI connection
- If successful, send a signal to Arduino to start the conveyor belt
- Initialise the camera and the classifier

On Receiving a Capture Request from Arduino

- Capture a photo

On Capturing a Photo

- Classify the image using the network
- Show the top result to the user and get the user input
- Write both the user input and classifier result to a text file
- Send a signal to the Arduino to activate the conveyor belt (proceed request)

9.5.5. Arduino code

Arduino codes are programmed to perform instructions on Android operating system

Setup Function

- Initialise the WiFi server and connect to the WiFi hotspot of the Android device

Loop Function

- If the system is not initialised, wait for a signal from the Android application to initialise the system
- After receiving the signal from the Android app, activate the conveyor belt until the obstacle sensor detect an item
- When an item is detected, stop the conveyor belt and send a signal to the Android app to take a picture (capture request)
- Wait for the “proceed request” from the Android app.

Also, in Figure 7, a sample code is shown which is used for Wifi connection between the P20 Pro system and the Arduino server.

ArduinoWiFiConnection

```
  }
  //client.flush();
  Serial.println("\tItem detected...");
}

void initializeConnection()
{
  // Check if a client has connected
  WiFiClient client = server.available();
  if (!client) {
    return;
  }

  // Wait until the client sends some data
  Serial.println("Initialising...");
  while (!client.available()) {
    delay(1);
  }

  // Read the first line of the request
  String req = client.readStringUntil('\r');
  //Serial.println(req);
  client.flush();

  // Read the request
  if (req.indexOf("/initiate") != -1)
  {
  }
  else
  {
    Serial.println("Invalid request");
    client.stop();
  }
```

Figure 7. Arduino code used for WiFi connection

9.6. Conceptual and prototype apparatuses

Two apparatuses were set for two working configurations namely; 1) conceptual stage and 2) prototype stage. In the earlier stage of the project, the first one was designed and implemented. The aim of this stage was to prepare for its subsequent stage which is more detailed and practical. Given the results from the first stage, an improved version of the system was developed which is more suitable for a working environment. Both test beds are explained next.

9.6.1. Conceptual test bed

At this stage, the key software codes were written and tested and the network was trained.

The test bed setup used at the conceptual stage is presented next.

Conceptual stage setup

- Vision System (mobile phone camera)
- Printed images simulating real boxes of packaged meat
- Mobile application *'IP Camera'* available free from Google Play store
- Lamp to regulate and alter lighting on the images
- Tripod to hold camera
- Mount to attach camera to tripod
- Laptop with MATLAB software and code required for the live stream and classification of the captured images (Figure 8).

Figure 8. Network learning at conceptual design stage (notebook + image)

9.6.2. Prototype test bed

An important part of the prototype is HUAWEI P20 pro smartphone (integrated system) that will be explained next.

P20 HUAWEI Pro integrated system

The P20 Pro Integrated System is a compact solution which allows an efficient integration of advanced camera, on board image processing, touch screen user interface, data transfer (networking), network learning, classifying (identifying the required label) and suggesting it as an option to the operator.

The Smartphone has an Octa core Hisilicon Kirin 970 Processor with a 6 GB of RAM, 128 GB of internal storage & Mali-G72 MP12 graphics processor. The unit runs smoothly even the most memory intensive applications with no lag. It has a 6.1-inch screen, protected by a durable Scratch Resistant glass, with AMOLED capacitive display having a resolution of 1080 x 2240 at 408 ppi. A key feature of Huawei P20 Pro is its dual primary camera of 40 + 20 + 8 megapixel and 24-megapixel front Camera

Prototype test bed setup; modular conveyor; FESTO

- Vision System (P20 pro camera)
- Printed images simulating real boxes of packaged meat
- Mobile application *'IP Camera'* available free from Google Play store
- Lamp to regulate and alter lighting on the images.
- Side mirrors to reflect the image into the camera
- Mount to attach P20 Pro to tripod

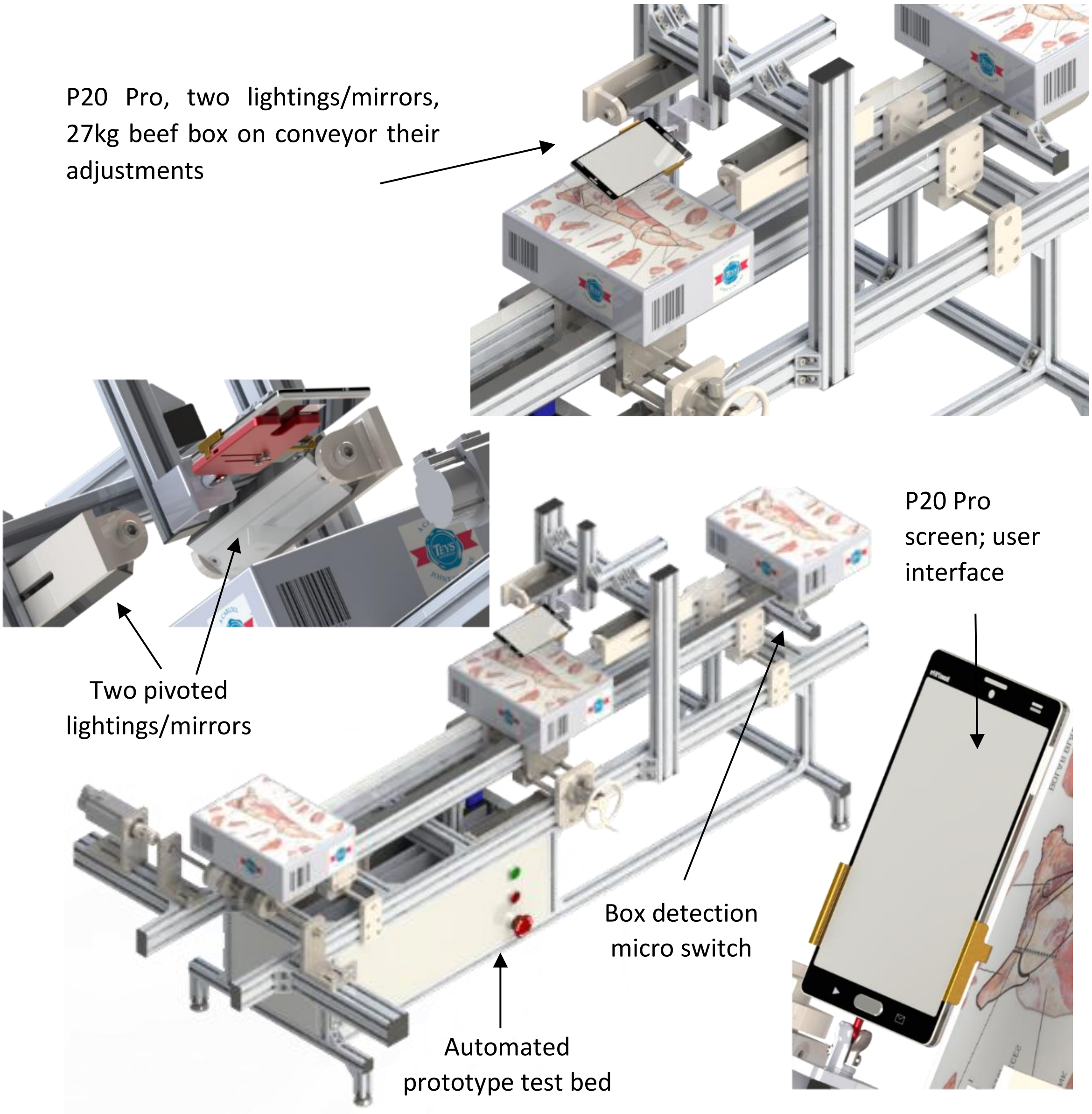


Figure 9. Network learning at the prototype stage (conveyor controller connects with the mobile wirelessly)

A structural diagram of the imaging system is shown in Figure 9. This demonstrates the components for the boxed beef quality quantisation system in an operational configuration. Elements of the prototype test bed include: HUAWEI P20 Pro integrated system (e.g. Camera and user interface), processor, drive control, printing labels, boxed beef, indexing table (conveyor), lighting stage control, image display, side mirrors, control display and micro-switch detection. Once the box comes in proximity of the switch, as it passes through the HUAWEI P20 Pro system, the box is detected and the conveyor is stopped for image processing, primal cut recognition, classification and issuing/recommending a label to be printed and affixed to the box.

The current test setup is based on the FESTO MPS500 conveyor belt loop consisting of four straight sections, designed to transport work pieces or pallets. The loop has six 'stations' at which point there are sensors to detect the presence of work pieces. Each of the four sections is driven by a geared three-phase motor.

Overall flow of the programme: When the IR sensor detects a box, the arm of the servo motor rotates by 90 degrees to halt the detected box. Then the Wemos board sends a message to the Android application to take a photo. The Android application takes photo in the background and shows it in the Image View in the right side of the screen. Then the captured image is sent to the deep neural network for classification. After determining the classification, the text field below the Start button displays the identified classification. The user is then allowed to select a custom classification or confirm the classified result by tapping on the buttons provided.

A sample user interface view, after completing the classification is shown in Figure 10.

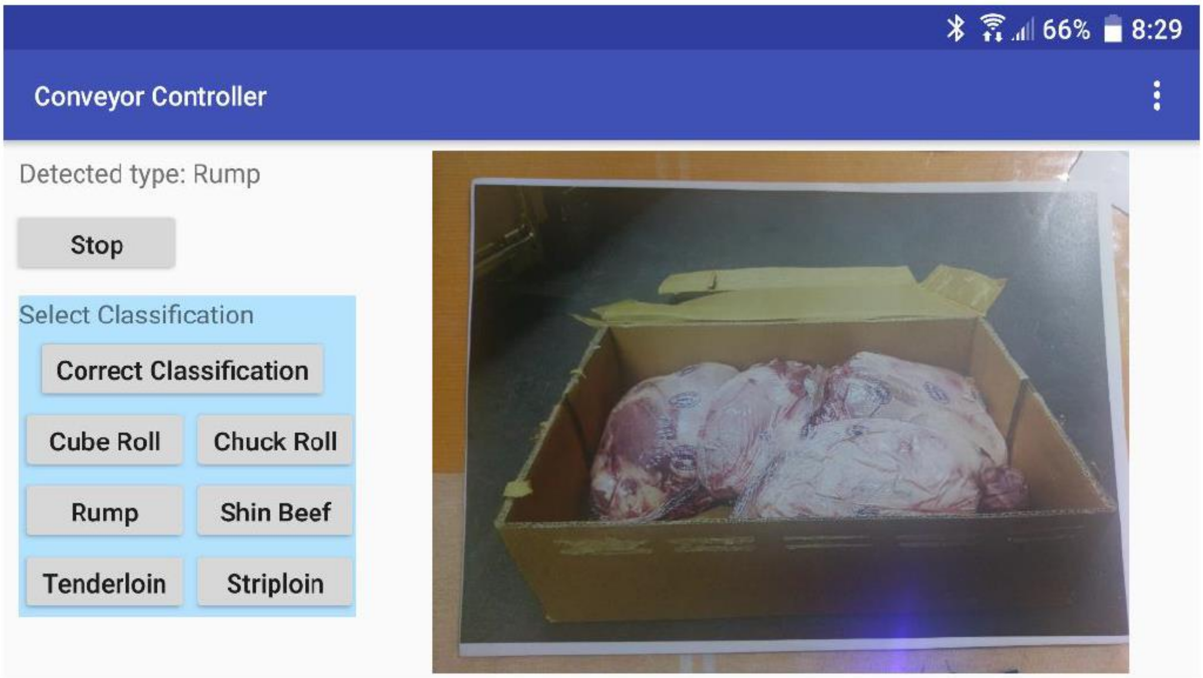


Figure 10. A snapshot of the user interface when the beef cut has been identified by the network. The user can confirm the identified type or correct the label if needed.

Once the user has confirmed/ changed the identified classification, by touching the relevant activated classification button (or correcting it), the servo motor places the box in its original position on the convenor to allow its motion for the rest of packaging operations. Next, the options on the user interface are disabled to prevent user from tapping them again. This procedure is repeated until the user stops the Android application by tapping on the “Stop” button. At this prototype stage, the user needs to reset the Arduino server manually by pressing the reset button on the Wemos board. The file which store the classification results and user selected results is stored in Download folder with the name “Classification.txt”. Figure 11 shows the prototype after detecting a cut type and suggesting its classification (Rump).

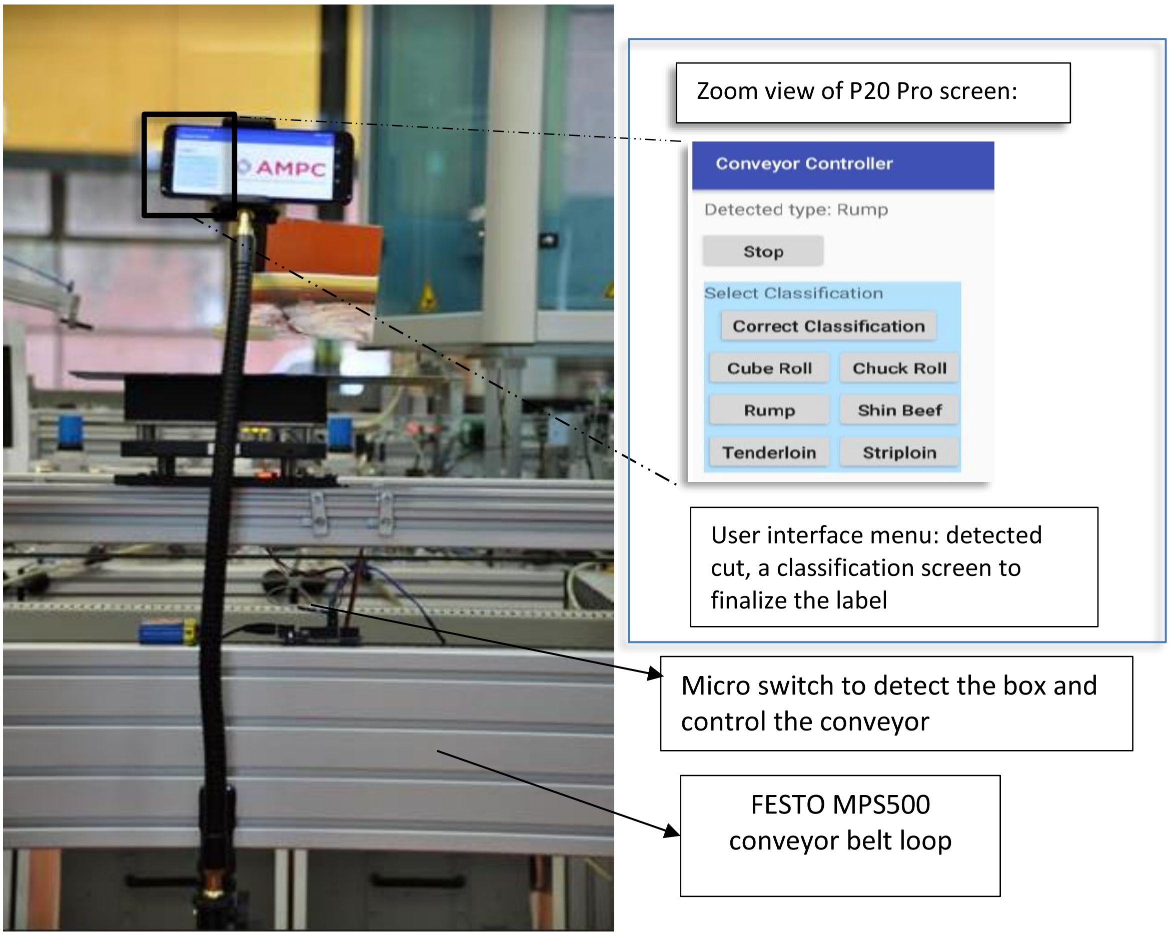


Figure 11. Prototype test bed in operational configuration

Figure 12 shows representation of a sample “beef in box” package by the top view image of a box. The image is reflected to the HUAWEI P20 pro mobile system using a side mirror positioned properly with respect to the box, conveyor and the mobile. The image attached to the conveyor is stopped after it is sensed by a proximity sensor until the cut is identified by the system. The user interface graphic software in the mobile identifies the cut and suggests it to the operator for confirmation/correction.

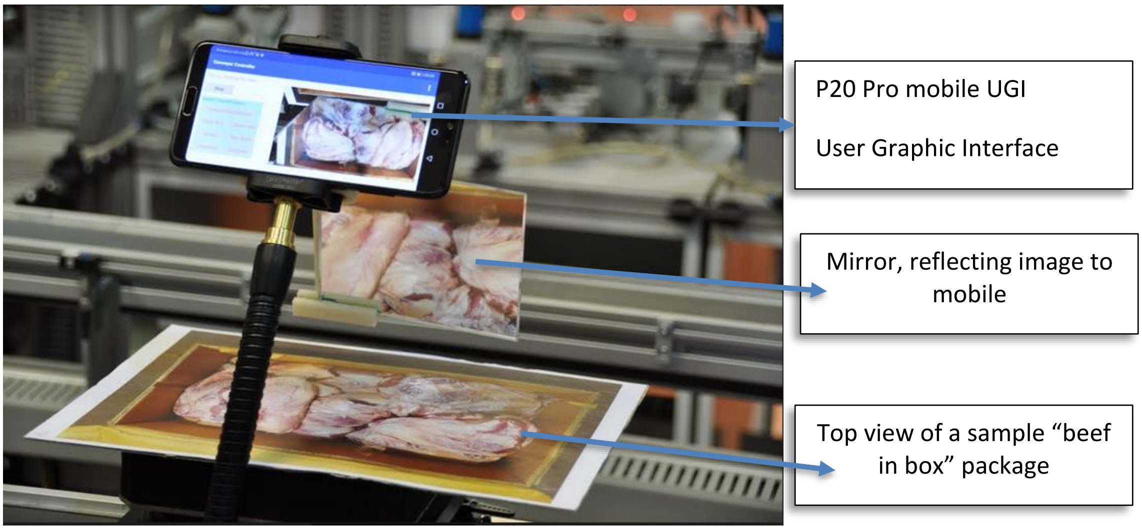


Figure 12. A close up view of, the conveyor loop with HUAWEI P20 pro system, mirror, holder, image of a beef in box.

9.7. Experiments

Figure 13 shows a varying number of photos of nine cuts which were acquired for demonstration and test of the prototype. This has been purely dependant on the stock available during test training of the network. The highest count is ~ 190 images, with 5 classes somewhere around the 150-photo mark.

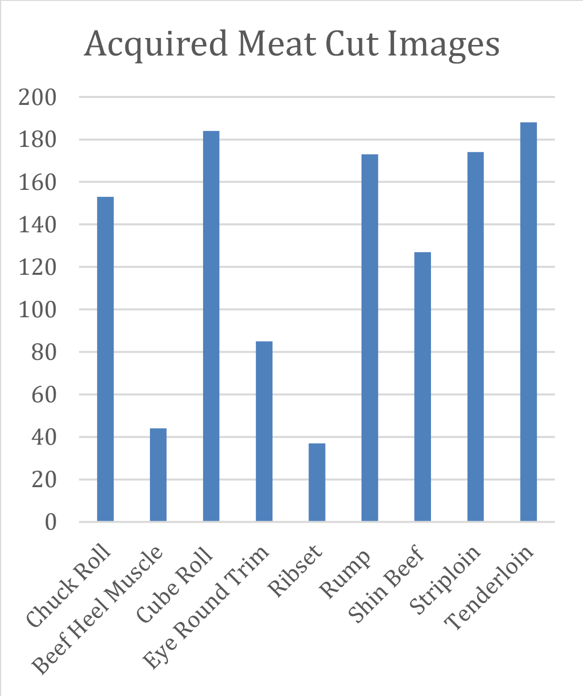


Figure 13. Meat images acquired to build the prototype.

For demonstration, it was assumed that the camera is at a fixed height, fixed angle, with relatively fixed lighting conditions, and the test and therefore the training photos reflect this. Otherwise there will be a need to train the network to compensate for all these factors.

Figure 14. Example images of 'Rump' Cut, taken from short edge, various Angles.

Images were taken from an approximately set height, and only varying the angle slightly, to simulate images from different times as they travel under the camera on the production line. Images were also taken from the long, and short edge of the packing box, as demonstrated in Figure 14 and Figure 15.

Figure 15. Images of ‘Rump’ cut, taken from long edge, various angles.

9.8. Network training

A “pre-trained convolutional neural network”, AlexNet CNN, was utilised for the first stage of this project. The network consists of 25 layers and can be utilised in MATLAB environment. The CNN used at the “detailed design stage of the project” (prototype test bed) to transfer learn in the prototype stage is Google Inception V3, which is trained on ImageNet database. The “network’s transfer learning technique” was utilised via a customised code. The code was developed during this project to adjust the last 3 layers. It enabled the CNN to read and learn from an existing meat cut image database. The database developed for demonstration experiments included different cuts and quantities, as seen in Figure 13. Sample cuts for the experiment included 6 cuts with the highest number of available images (see Figure 13).

As a preliminary trial, the net was retrained with only two classes of beef, ‘Rump’ and ‘Cube Roll’. The Net was able to label all of the images with 100% accuracy. The early experiments were performed on a personal laptop and took approximately 12 hours for the training and treatment of the images.

9.8.1. Project’s GPU server

The next test involved training of the network on all 6 classes of meat that would be included in the final product. This required high computational resources. To perform the full training, a dedicated GPU server was established for the project and used which enabled to complete the network of all 6 classes of different beef cuts. This allowed quick assessments and alterations to the code to make it functional at an optimum capacity. In both tests, the images were acquired and resized to the expected size by the CNN, which is 227 x 227 pixels. The resizing was performed automatically by a MATLAB scrip which reduced the processing time considerably in comparison with manual one.

A snapshot from a sample user interface is presented in Figure 16 which shows a step to set up the WiFi Arduino server’s IP for wireless communication.

Figure 16. Setting up Arduino server's IP.

A new transfer learning code was developed to complete the trainings via the GPU servers. This enabled the training for all 6 classes. A "pseudo image database" was developed for the experiment. The database consisted of a total of 1000 images, split among the 6 classes. These images were separated into two sets, one for training, and one for testing. This was performed via a MATLAB script to randomly select 80% of images from each class, and use this for training, the remaining 20% was used for the testing. It produced a final classification accuracy of 96.5%.

Table 1. Confusion Matrix for trained network.

Legend	
(green)	Correctly Classified
(orange)	Incorrectly Classified

		OUTPUT							Total Input Images	% Correctly Classified
		Chuck Roll	Cube Roll	Rump	Shin Beef	Striploin	Tenderloin			
INPUT	Chuck Roll	30	1	0	0	0	0		31	96.77419355
	Cube Roll	0	35	1	0	0	0		36	97.22222222
	Rump	1	0	34	0	0	0		35	97.14285714
	Shin Beef	0	0	1	24	0	0		25	96
	Striploin	2	0	0	1	32	0		35	91.42857143
	Tenderloin	0	0	0	0	0	38		38	100
									TOTAL	TOTAL
									200	96.5

The chart in Table 1 is the confusion matrix based on the above network training experiments. It shows the inputs to the system in the leftmost column, and the outputs in the first row. The output comprises the number of samples that were classified correctly (green) and incorrectly (orange). This shows the network's accuracy in classifying each specific class (e.g. in the fifth row: with an input of 35 images of the cut 'striploin', 32 correctly classified as striploin, 1 incorrectly classified as shin beef, and 2 incorrectly classified as chuck roll). This matrix provides more detailed information on the real accuracy of the trained network, and identifies where a possible improvement could be made by increasing the number of trainings. An advantage of deep learning is that the performance improves monotonically with the data; it is not limited by a saturation plateau by increasing the size of the database (Ng, 2015). This is depicted in Figure 17.

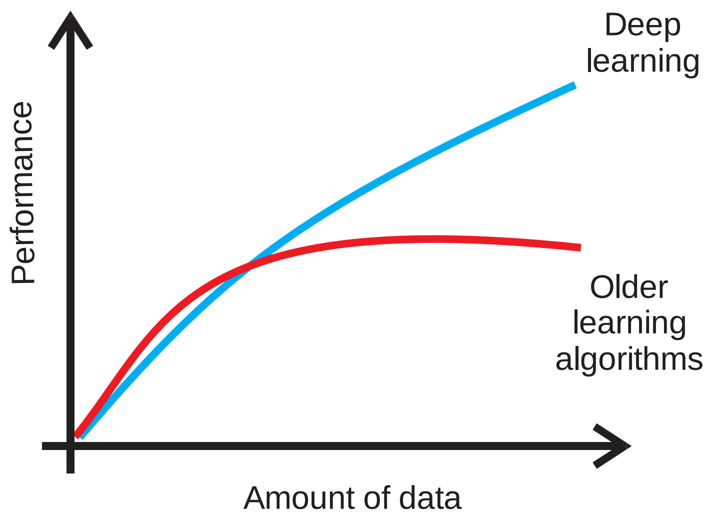


Figure 17. How do data science techniques scale with amount of data.

9.9. Final lab test and demonstration

A Final demonstration was held to show the final product in full working order, and to enable an analysis of its accuracy in real world situation. The current accuracy given from the trained network is 96.5%, but this accuracy is from image files uploaded directly into the system.

In this real-world demonstration, the accuracy is slightly less, due the other external (not related to the process) factors such as;

- Inclusion of surrounding information in the image which will be inevitably sent to the trained network for analysis
- Lighting condition, on the printed images, impairs the accuracy.
- During the demonstration, the images were printed. This process reduced resolution of the image, caused loss of image quality, size, and some distortion of shape.

The industrial scale system will however not be limited by these issues.

9.10. Future improvements

The results shown in the previous section can be improved in future by considering the following suggestions:

- Better resizing of the image to reduce loss of detail and to reduce image distortion.
- Calibrated and set camera height to capture the images and the actual meat products and to reduce background distracting images.
- Consistent light source as would be seen in the onsite application.
- Testing on real product boxes, instead of printed images (the printed images would have very reflective surfaces, and therefore lighting played a large part in misclassification issues, this would be avoided if tested on real cuts)
- Use a higher resolution camera for the image capture: current test setup has original photos taken on 12MP camera, then printed, then re-digitised via 12MP camera, then resized, and then classified, this process reduces the details, increases distortion and contributes to other unwanted effects.

10. APPENDIX 2- A FEASIBILITY REPORT OF THE INTEGRATION OF THE BOX INSPECTION DATA IN AN OVERALL SLAUGHTERHOUSE OPERATION

In this appendix, the feasibility of the integration of the box inspection data in an overall slaughterhouse operation and its associated "total cost of ownership" (TCO) are discussed at a "qualitative" level. Details and "quantitative" cost-benefit analysis specific to the proposed intelligent technology could be found in the second milestone report for this research.

10.1. Implementation/integration: cost-cutting measures for more profit

There are many benefits and costs associated with a pre-defined industry solution for the meat sector (see for example (Wood, 2018b)). Typical modules for a Smart MEAT Factory; step by step from vision to reality can be found in (Wood, 2018a). As far as an optimum management of business processes for smart beef production is concerned, several models including Horizontal, Vertical, Modular and scalable have been proposed (Wood, 2018c).

Intelligent automation is a key part of the technology proposed in this research and has to be integrated in a larger total system at the industrial level. The process involves converting the non-digital signals from an imaging sensor (e.g. UV, IR, XR or ultrasound) to digital signals. They are transformed mathematically to a final digital image. Next, the images are stored and processed for machine vision systems which comprise of the following steps:

- Read the raw images from the database.
- Enhance and segment them for desired information.
- Identify textural, morphological, and/or colour features of the images.

The identified features are used to classify the samples and are typically fed back to adjust the image acquisition to improve performance of the system (machine learning).

Some spinoff applications for machine vision automation include:

- Automated quality control of meat cuts
- To optimise raw materials and products
- Seamless documentation of quality data
- Assisted automated (intelligent automation) "item recognition" in unloading
- Cutting item recognition at cutting exit

A key pre-requisite step for labelling operations is cutting. The labelling and cutting steps and their automation are pivotal for profit and loss. State-of-the-art planning modules and total systems (e.g. ERP) require improvement to provide their corresponding digital data and information. The modules consider information from procurement, inventory, production and sales to identify the needed primal parts for cutting. As a result, overstocks with high inventory costs are minimised which in turn reduces capital commitment.

Two key existing total systems for production and manufacturing industry include Materials Handling System (MHS) and Enterprise Resource Planning (ERP). Several abattoirs have adopted these to plan their production.

10.1.1. MHS

Mousavi et al. (Mousavi et al., 2002) discussed developments in tools and techniques to improve the production process in handling and cutting meat portions for end users. They suggested to employ an existing “material handling systems” (MHS) and their software/hardware, logistics and technical requirements for tracking meat cuts in a production process. They proposed to employ such established tools and techniques as a practical solution for the development of a tracking and traceability system within the meat industry. They suggested that this system is capable of identifying and handling a product and the information attached to meat cuts throughout the production process to retail packs.

10.1.2. Enterprise Resource Planning (ERP)

Enterprise Resource Planning (ERP) started in manufacturing industry, but extended so quickly to address many other functions and sectors. To implement a vision based automation in an ERP application involves organisational change which mainly focuses on the ERP system. The system can simply be described as an integrated information system that serves all aspects of the industry. It involves management of transactions, maintenance of records, provision of real time data and facilitation of planning and control. However, its effectiveness is an outcome of the success of the implementation life cycle.

Australian meat industry has already started integration of the ERP systems and automation of the box inspection data is one of the few missing links to extend the current slaughterhouse operations into “full Enterprise Resource Planning (ERP) system”. The implementation involves many internal and external factors and has a great impact on the industry in terms of the risks involved and the opportunities provided. Successful ERP implementation requires an integrated strategic framework. The box integrity checks and inspection data have to be integrated into an existing SAP, MHS, ERP or a similar system. Therefore, its feasibility depends on how it can operate within the systems, applications and products. Also it depends on what costs are involved and what are advantages and disadvantages of the integration. The costs and benefits of the total system is discussed next. Due to similarities between SAP, MHS, ERP or other similar “total systems”, we refer to the existing system as the *total system* in the subsequent sections.

10.2. Costs & benefits of a “total system” implementation and TCO

To own an ERP project, there are several visible and hidden costs which constitute the “total cost of ownership” (TCO). A feasibility analysis to integrate the automated solution suggested by current project in an existing ERP or as a total ERP solution will be analysed here.

It is difficult to manage and measure the success for such an implementation. Two sample implementation analyses are reviewed here for the sake of completeness. Harwood et al. (Harwood, 2017) provided a case study implementation, which gives a picture of what is involved in an implementation, starting from the realisation that there is a need to embark on this course of action. The process enables the management to anticipate potential problems and hopefully avoid those. Typical costs, the time and resource consumption by the integration (the second sample implementation analysis) are discussed by Chakraborty and Sharma (Chakraborty and Sharma, 2007). The suggested integrated strategic framework that was tested through a case study can provide effective parameters that need to be addressed for a successful ERP implementation. The research also provides theoretical specifications for generating a cumulative body of knowledge in the ERP implementation area.

Total cost of ownership (TCO) is one of the key financial estimates. It helps buyers and owners to determine the direct and indirect costs of a product or system. This "management accounting concept" is typically used in full cost accounting where it includes social costs. TCO is a serious consideration and there are many parameters which should be taken into account to minimise the cost.

Three main phases can be defined for the ownership:

1. Acquire and implement
2. Operate and maintain
3. Replace

There are various parameters which affect TCO.

In general, the cost grows in the acquisition phase as the system is implemented. Costs are high at the start of the project as the software and hardware is acquired and implementation takes place (Anderson et al., 2009).

The costs reduce when the teams are formed and work together; they reduce to a certain extent when the life cycle starts (after go live). During the maintenance, the costs increase due to the needed trainings and any full reductions as a result of re customisations. Finally, during the replacement phase, the costs increase again. This is when all or some modules need to change.

10.3. What influences the TCO?

The first factor is transaction volume both now and in the future (scalability). The industry has to guard against the flexibility in demand to allow a seamless temporary expansion or contraction of the operations. (Anderson et al., 2009).

TCO is also affected by the number of users: "more users" means more data to process and more input-output facilities that are needed. It is also affected by the functionality of the software: the number of modules that the industry has to buy. Various types of modules that can be added to a total system include:

- Human Resource.
- Inventory.
- Sales & Marketing.
- Purchase.
- Finance & Accounting.
- Customer Relationship Management (CRM)
- Engineering/ Production.
- Supply Chain Management (SCM)

Some other key cost components of a total system include:

- the software and data based licenses,
- servers and network infrastructure to be provided,

- implementation services (e.g. consultants),
- internal HR costs,
- and ongoing maintenance.

There are some costs that differentiate one total system from another. Examples of these include:

- the cost of the software licenses,
- the cost of implementation services,
- the maintenance costs.

For example, the above items are costs which are different between SAP or Oracle or the other vendors. However, there are some common issues for all total systems. These are not influenced by total system selection. Sample vendor-independent costs are:

- database license costs,
- internal HR costs,
- and hardware costs.

This can be understood by noting that the industry will need the hardware no matter who provides the needed software. Having said that, there are some ways to reduces these costs. For example, if a software is chosen as a service solution. This reduces a need to have a large IT division but these costs savings could be insignificant.

10.3.1. Implementation

During the implementation process, at the beginning, there's a high risk of failure due to participant resistance and from the impact of high cost on the industry resources.

Strategies should be employed to show the benefits at the early levels of implementation. An example is shown in Figure 18. It depicts processing of an input (left) to deliver the product (right) over a period of time (horizontal). The political sensitivity of this operations is shown in the vertical direction. The implementation strategy is to seek a higher volume of the staff driven by the top at day one to achieve some early win using the new process; this early win involves a process which is known to be faulty. Improving this process will be noticed in the company and will help the industry to implement the system for other inputs/buy-ins. An example applicable to this research is to assign higher staff at the early stages of the implementation to rectify the mislabelling and integrity checks using the new system. Once the rejections are reduced, the system gains a higher momentum to integrate the new system using a lower number of staff.

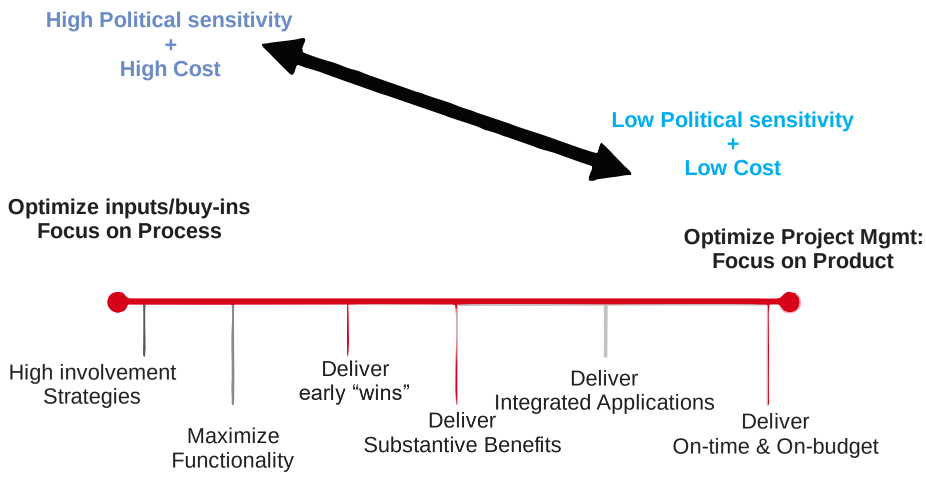


Figure 18. Total Cost of Ownership; implementation strategy

10.3.2. ERP costs vs time

Figure 19 shows an analysis for total cost of acquisition of implementing a total system (Anderson et al., 2009). On the left hand side, some one-time acquisition costs can be seen. The cost of software and hardware fall in this category. Also, there are some reoccurring costs which need to be accounted in the total cos.

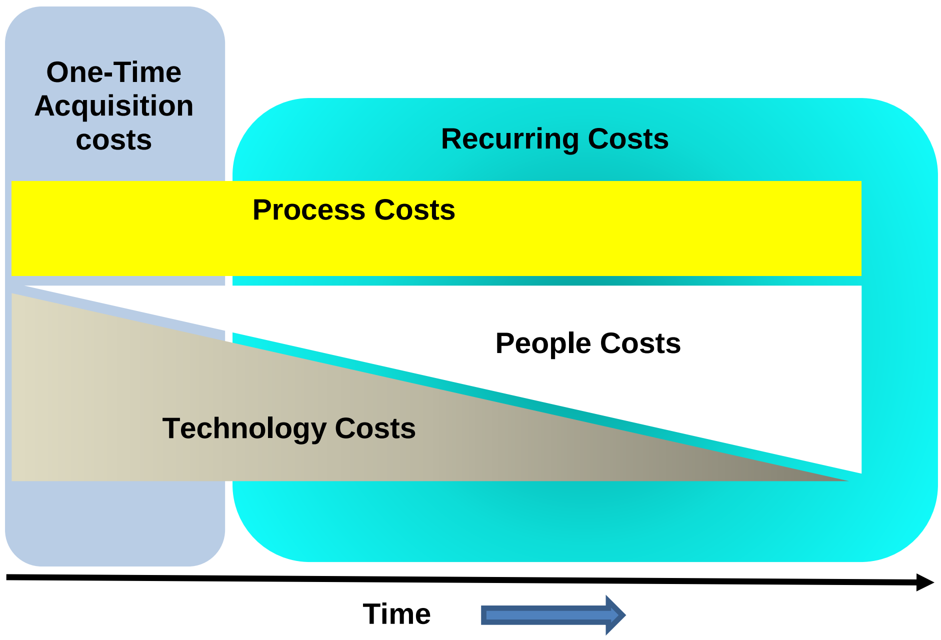


Figure 19. A generic TCO analysis to implement a total system

Process costs: In theory, they should decline but a constant value is shown here; these are the kind of costs in running a particular process. In an ideal case, the process costs reduce after some time when better processes are established.

Technology costs: these are significant at the beginning and reduce at later stages. Technology items for this particular project were introduced in other parts of this research (first and second milestone reports and Appendix 1 for the current final report: technology demonstration). These also include the technology needed for the infrastructure such as networks and servers.

People costs: conversely the people cost is quite small with pilot projects. As the project is about to go live and past it, people training incurs significant costs. As such, their progress is reverse to that of technology.

10.3.3. Application licensing

Licensing costs for the software depend on the number of end users of the system and also “the number of implemented modules”.

As an example, the industry has a core total system in one particular case then modules of supply chain management and customer relationship management are added. The number of employees that actually will need to use particular modules of the software are typically much less than that initially has stated. This results in overestimation of the needed licenses.

There are typically three different types of license to choose from:

1. named user
2. site license; which means everybody can use it obviously more costly
3. concurrent user; where a given number of users (say 200 users) can use the system

When the industry is a heavy user of the software, the following licensing considerations should be taken into account:

- heavy user not a casual user license
- there are volume discounts available for multiple module purchases so it's well worth thinking about that when the order is being made
- and end of quarter discounts from the software vendors who have met their targets

In the last case, the software provider is looking for some value that can add to their sales record. This means that the industry may be able to perform the integration slightly cheaper from a software point of view and licensing.

10.3.4. Database, OS and identity management

Key pre-requisites for the total system include databases, operating systems and identity management.

The database cost is based on

- the number of simultaneous users logged in
- the number of database servers required

The costs of operating systems are also user related because the industry has one operating system per computer.

Identity management is essential for two main reasons:

- to allocate rights and privileges by the role
- to give access to software modules

10.3.5. Computing hardware

Before a system goes live for production use, the system needs to be verified in terms of whether its infrastructure is structurally sound and "designed for run." Infrastructure testing involves mainly the computing hardware including:

- database and application servers (or web boxes)
- storage systems (e.g. four-way raid system)
- network infrastructure
- wiring and power supply
- user workstations
- redundant systems (i.e. backup for backups)

Also, are some auxiliary hardware such as diesel generators, power supplies for battery backup to support these systems, fire safety, etc. Some of these costs can be avoided by acquiring software as a service (Hosted total solutions).

This project provided "computational test beds" at two levels: conceptual and prototype. More work is needed to commercialise these test beds ready for implementation.

10.3.6. Implementation services

Implementation costs are difficult to estimate. However, "statistical based models" and common costs in similar cases can be used as a guide. Existing statistical data are used to develop models and to estimate the cost of implementation (Holland and Light, 1999) and (HassabElnaby et al., 2012). Based on several case studies, an "implementation ratio model" has been developed. The model predicts that for every dollar of software license cost that the company pays for its total system, two dollar has to be allocated to cover implementation costs. Implementation ratio estimates are reflections of the complexity of the software installed and the processes involved. Therefore, the ratio should be higher for complex software and processes.

Typical implementation costs relevant to services include:

- implementation specialists
- subject matter experts
- project managers
- testing and training specialists

The costs will rise exponentially if consultants are used indiscriminately; some consultants basically using the industry as a way to learn. This is also the case if the industry is not ready to use consultants when they arrive.

Another technique is to ask consultants for a cost ceiling to limit exposure which prevents spending money above a known limit.

10.3.7. Internal human resource costs

Internal human resource (HR) costs associated with the implementation are also difficult to estimate. An obvious and significant cost is due to the loss in productivity of functional teams; some team members have to work in new teams to implement the new system. The industry typically assigns its best personnel for the new system while they have to use the old system to perform their normal daily jobs. This incurs cost of diverting employees from their jobs.

Internal secondment and backfilling the positions temporarily can reduce the costs. This also allows that the personnel to go through the cycle of design configuration testing and training.

The cost of employees on a project can be estimated as outlined below.

The full-time equivalent (FTE) staff can be seen as the "parts" of employee seconded to the project both during implementation and after completion of go-live. The FTEs is calculated as:

EFTs = % "member project time" × "duration of the service" × "the headcount"

To estimate total internal labour cost for these employees, their skill level and the labour rate should also be considered.

10.3.8. Ongoing maintenance

The cost of maintenance after the go-live can be estimated as a percentage (say twenty to thirty percent) of the total system software's cost. This cost is comprised of the following components:

- updates
- patches
- routing consulting
- technical support
- and minor upgrades

10.3.9. Hidden costs

There are several hidden costs for implementing a total system which results in underestimation of the TCO. Some of these are discussed here.

10.3.9.1. Scope creep

A key hidden cost is "scope creep". This is the cost that was originally unplanned. Scope creep has to be challenged to prevent "poor business requirements gathering" and to avoid failure of the implementation. Scope creep happens when the definition of the project becomes too wide and the industry has to pay for them in terms of delays and extra cost for extra modules.

Other factors influencing scope creep include client non-readiness and unavailability of the hardware infrastructure. The later includes hardware and the remote connectivity to run the system.

10.3.9.2. Training

Training is another component that can lead to underestimating the TCO. Quite commonly, the firms severely underestimate the training they need. The cost of training however can be reduced when the firms seek help from the total system training specialists to ease the transition from old to the new system. However, skimping on training can lead to problems and unplanned future costs so it has to be considered very carefully.

10.3.9.3. Customisation

Some hidden implementation costs can arise which are associated with customisation. Examples of these include a situation in which a firm may not examine the full functionality of the new system.

Also, the industry may only see the need for customisation after the project has started. Another case is when the industry needs a standard code to be changed. However, code changes could easily hold up the projects and involve costly consultants. Also, future upgrades can become problematic if the standard code is customised (non-standard code). The vendors of a total system always claim that they provide the best practices out-of-the-box (a black box solution).

10.3.9.4. Data management

Data management and cleansing in the traditional systems (non-total) are very expensive. A key benefit of the total system is that the system offers a centralised data and eliminates data redundancy. These reduces the data costs dramatically. The system makes sure there are no duplicates, missing entries, invalid entries or typographical errors. These can be done automatically using a cleansing software that checks data with a known list of entities.

10.3.9.5. More causes

A tailored system is extremely costly due to its modified interface design. A bespoke interface design (e.g. due to a need for composite applications) may need to be linked to external and legacy systems. These also include other total systems.

Another operation that increases the costs includes writing customer reports. This explains why an industry needs to know all needed reports before going live. Having said that, reporting software in many cases are offered as "modular" add-ins simply because reporting is an ongoing process which is subject to constant changes due to the customer need changes.

10.4. Benefits of the total system

In the second stage of this research project, a model based quantitative cost and benefit analysis were carried out to estimate the costs and benefits on mislabelling and package integrity checks and documentations of beef in boxes. In the current report, the feasibility is the major focus.

Benefits of the total systems are numerous and they have been adopted by many industrial sectors despite their sizes or the type of their activities. However, the challenge remains to quantify the benefits. In fact, their costs are easier to quantify than their benefits. Many benefits are intangible such as better data integration. Industries often adopt a total system to limit the project scope to address lowering inventory costs and a faster time to close the books. The latter is also an advantage as it protects other elements form future phases of the project against a scope creep.

One way of evaluating the impact of the implementation is to compare the "As Is" situation to the "to be" situation. Some Key Performance Indicators (KPIs) for evaluating the current and future performance of the business include: inventory turnover, order to cash cycle time, order fulfilment versus time (before and after go-live). These KPIs can be tabulated before and after implementation to provide a better vision on benefits of the implementation.

10.4.1. Benefits

Three key and sequential benefits of a total system are efficiency, effectiveness and better service (See Figure 20, (Meyer, 2002)). Each stage increases the potential benefits that accrue from the implementation. Many industries finish their total system implementation after "go live", but it is actually at that point that the real benefits from extending the system can be harvested. After the first stage, incremental improvements start due to a synergic combination of efficiency and effectiveness (second stage). In the third stage, a combined efficiency, effectiveness and services will extend the industry's capabilities. These could create new capabilities which can change the game for the industry.

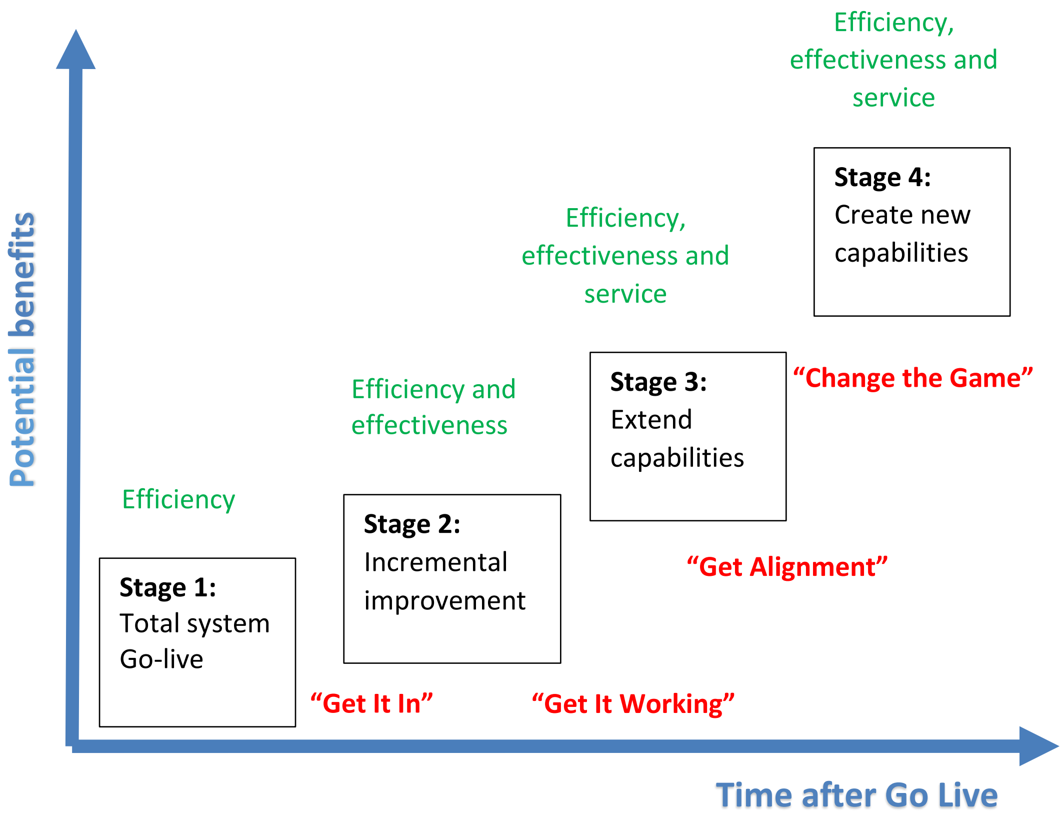


Figure 20. Benefits of a total system after go-live (Meyer 2002)

10.4.2. Integrated financials

There are several benefits in having an integrated financial information. This is in contrast with using multiple spreadsheets different versions of revenue numbers by different departments. Once there is an integrated financials, then the data is trusted more and only one definitive set of revenues and numbers is used by everyone. Therefore, an integrated financial system increases the overall trading efficiency of the group and the system. The integrated data also reduces time to close a given operation.

10.4.3. Integrated orders

The total system handles customer orders in a set of seamless sequences including: sales, credit, picking, packing, shipping, invoicing, cash, receipt, etc.

Before implementation, an order could easily halt in an inbox, or could be lost. Departments might create excessive handoffs and data duplication. After implementation, one source of information allows easier order. This reduces the ratio of order to cash cycle time, increases profits through lower costs and improved efficiency. This is a result of reducing Work in Progress (WIP) which eventually reduces scrap and rework.

10.5. Faster processes

The total system standardises and accelerates the slaughter house operations; it enables standard methods for automation and prevents packing of the same cuts differently by different regions.

Sharing the same network training between different abattoirs, the processes and packages (products) become standardised. Integrity checks, quality data, their documentations and schedules are kept and rework is minimised.

10.5.1. Reduced inventory

One highlight of a total system is that it leads to a dramatic reduction in the inventory. This is a key milestone and is an indication of a near ideal status called just-in-time manufacture (Sakakibara et al., 1997). When the inventory is reduced, the customer bears the cost of storing the supplies that the company needs. Obviously, the customers only bear that if they are receiving good orders from the industry. Some expected outcomes are: optimisation of order fulfilment and reduction of raw material usage (Kannan and Tan, 2005). Also, the "beef in box" exports become more consistent hence warehouse stocks at abattoirs and docks stabilise. The functionality of supply chain further helps management of the inventory. These increase the smoothness in flow of the processes, reduce work-in-progress, reduce waste and rework which eventually prevent significant costs for the industry.

It is a well-known fact that just in time, supply chain management, and quality management (e.g. total quality management) are correlated, and they impact business performance (Kannan and Tan, 2005). Kannan and Tan used "factor loadings" to show the above correlation. Factor loadings (factor or component coefficients) are the correlation coefficients between the variables (rows) and factors (columns) (O'Rourke et al., 2013). Sample factor analyses by Kannan and Tan based on "just in time" (JIT), "total quality management" (TQM) and "supply chain management" (SCM) are shown in Figure 21, Figure 22 and Figure 23, respectively bellow.

Factor	Scale item	Factor loading
JIT 1: material flow	Reducing lot size	0.794
	Reducing setup time	0.756
	Increasing delivery frequency	0.680
	Buying from JIT suppliers	0.533
JIT 2: commitment to JIT	Increasing JIT capabilities	0.833
	Helping suppliers increase their JIT capabilities	0.814
	Selecting suppliers striving to promote JIT principles	0.565
JIT 3: supply management	Selecting suppliers striving to eliminate waste	0.832
	Reducing supplier base	0.579
	Preventive maintenance	0.551

Figure 21. Factor analysis using Just in Time (JIT), (Kannan and Tan, 2005)

Factor	Scale item	Factor loading
TQM 1: product design	Modular design of component parts	0.844
	Using standard components	0.774
	Simplifying the product	0.719
	Designing quality into the product	0.637
	Considering manufacturability and assembly in product design	0.631
TQM 2: strategic commitment to quality	Employee training in quality management and control	0.830
	Empowerment of shop operators to correct quality problems	0.807
	Top management communication of quality goals to the organization	0.780
	Emphasizing quality instead of price in supplier selection	0.555
TQM 3: supplier capability	Considering commitment to quality in supplier selection	0.780
	Considering process capability in supplier selection	0.746
	Considering commitment to continuous improvement in supplier selection	0.694

Figure 22. Factor analysis using Total Quality Management (TQM), (Kannan and Tan, 2005)

Factor	Scale item	Factor loading
SCM 1: supply chain integration	Seeking new ways to integrate supply chain management activities	0.845
	Improving integration of activities across supply chain	0.771
	Reducing response time across supply chain	0.751
	Establishing more frequent contact with supply chain members	0.622
	Creating compatible communication/info system for supply chain members	0.525
SCM 2: supply chain coordination	Communicating customers' future strategic needs throughout supply chain	0.733
	Communicating your future strategic needs to your suppliers	0.730
	Creating a greater level of trust among supply chain members	0.669
	Identifying additional supply chains where firm can establish a presence	0.535
SCM 3: supply chain development	Participating in sourcing decisions of suppliers	0.757
	Extending supply chain membership beyond immediate suppliers/customers	0.737
SCM 4: information sharing	Using formal information sharing with suppliers and customers	0.752
	Using informal information sharing with suppliers and customers	0.728

Figure 23. Factor analysis using Supply Chain Management (SCM), (Kannan and Tan, 2005)

10.5.2. Other benefits

A total system creates a simple method for recruitment, training, employee time tracking and compensation management by consolidating all information and documents into one system. This will also provide self-service records accessibility for managers and employees.