Final Report

Bone Belt Monitoring

Bone Belt Monitoring – Vision RGB+NIR Stage 2

Project Code
2021-1175

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Published by
AMPC

Date Submitted
2022/05/30

Date Published
30/05/2022

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1.0 Executive Summary

The goal of the project Bone Belt Monitoring Stage 2 is to adapt and refine an existing high-end Vision Technology for monitoring the product stream on a Bone Belt by developing algorithms capable of determining the trim quality of the bones. The monitoring system will enable the meat processor to react to changes in yield performance and to identify problems in the operations of the boning room.

The chosen measurement equipment consists of a Multispectral Vision System with an RGB and NIR (Near Infrared) camera sensor. The Vision System was adapted and refined for Bone Belt Monitoring including a conveyor system and custom-made software for scanning different kinds of bones in movement.

The Vision System was first used to scan bones from lamb and cattle in a short series of laboratory pre-testing sessions performed at the pilot plant facility available at DMRI. During these sessions, the general procedures to be used in the subsequent larger-scale data collection sessions were developed, and the definition of a 5-scale trim score for describing and discussing trim quality was established.

Large boxes of both well-trimmed and very poorly trimmed bones from cattle were sourced from two local processors for large scale data collection at the DMRI pilot plant facility. All bones were scanned in all natural orientations, and a subset of bones was selected for specialized trimming and yield tests. In these experiments, each bone was trimmed in steps by skilled trimming operators to produce a progressively better trim quality, and the recoverable meat was weighed. At each trim level, the bone was scanned by the Vision System. The collected image datasets formed the basis of the subsequent algorithm development phase.

Additionally, separate experiments were performed to demonstrate the foreign object detection capabilities of the Vision System. Several low-density foreign objects of various size and texture were mixed in with the bone samples and scanned. Detection of foreign objects down to a few millimetres was successfully demonstrated.

Using the datasets from the data collection sessions, AI Machine Learning approaches such as Deep Learning Neural Networks were applied for bone type classification, as a high classification level enables improved yield estimate models for the specific type of bone segment. The classification models were able to correctly identify all different bone segments with a very high degree of confidence. Only non-overlapping bones were considered in this test, but the approach can be applied to overlapping and mixed bones as well with a targeted dataset.

Prediction methods for estimating the trim quality were pursued using different analytic strategies. At first, specific segmentation models were developed for estimating the meat-to-product ratio for a variety of bone segments at different levels of trimming. Secondly, the trim score was predicted using Deep Learning Neural Networks applying the “raw” image data. Both methods were capable of predicting the trim score for a range of bone segments, while the trim quality prediction for each individual bone was associated with some uncertainty, due to the borderline case of determining the exact trim score.

The weight measurements of meat from the yield experiments were used to develop a prediction model for estimating the potential recoverable meat from the trimmed bones at different levels on the trim score. A clear linear relation was found that can be used for quantifying the yield loss at the bone belt.

Monitoring the bone belt continuously allows a 1:1 evaluation of all identifiable bone segments that would offer significant additional value to the cutting floor manager’s sample control on the work from the boning room. For a given batch type, the overall performance can be monitored, while at bone segment level the (recoverable) meat-to-product ratio can be estimated. This enables target re-evaluation and ensures that corrective actions can be implemented to improve the yield in the boning room. Furthermore, for the processors using the bone products for further processing into human or petfood applications, it can be validated that unwanted foreign objects are detected and can be flagged for removal.

The business case and payback time for the individual processor will depend on many factors, e.g., the current level of performance in the boning room, the price of beef, production volume, the carcasses processed, and not least how well the users are able to use the data for a continuous improvement of the operation.

With the feedback of data on KPI's from the solution, it is considered feasible to improve the boning room performance at a typical processor to harvest additional meat product with a fast payback. Such an improvement is well in alignment with the global agenda of making more with less, and producing less waste, especially if the product stream is not for human or petfood usage.

In the subsequent project Stages, it is recommended to first install an in-line measurement equipment at an AU processor facility to further develop and test the solution on a continuous product stream, and secondly to validate the ability for in-line estimation of the potential recoverable meat.

2.0 Introduction

The goal of this Stage 2 project within Bone Belt Monitoring is to adapt and refine an existing high-end Vision Technology for monitoring the product stream of a bone belt and to develop algorithms for data modelling to be able to determine the levels of meat still attached to the bones. The monitoring technology will enable the meat processor to react to changes in yield performance and identify operation problems early on within the boning room.

3.0 Project Objectives

The objectives of the project are:

- Demonstrate the working functionality/capability of the measurement system in terms of estimating the meat-to-product ratio for a stream of bone products collected from the local industry. At first by lab testing in the pilot plant at DMRI and secondly, if feasible, a short-term data collection at a bone processing line at an EU processor reflecting the product representation and variation, either at-line or in-line.
- Identify 1 to 3 specific product types and estimate the meat-to-product ratio.
- Demonstrate the feasibility of simultaneous detection of foreign objects such as small visible plastics pieces, string, rope etc. in the product stream.
- Develop indicative targeted $RRP and draft a proposal for Stage 3 + 4, which includes an indication of a commercialisation pathway.

3.1 Project Background

The yield performance of a boning room can indirectly be monitored by what leaves the room on the waste belt. This method of removing by-products from the room is also a common way to forget mistakes at the boning line, out of sight, out of mind. In some cases, even foreign objects may end up on the bone belt; objects not fit for human consumption like gloves, string, plastic etc. causing additional issues and costs for the subsequent food business operator. A monitoring solution for both missed product yield and alerts for noncomplying foreign objects will create significant value for the food processors.

3.2 Project Description

The project objective aims to establish a functional model that continuously monitors the product stream of a bone belt and delivers estimations of key performance indicators, such as:

- Estimate the meat-to-product ratio for the continuous product stream.
- Use AI recognition models to identify one and up to three specific major bone segments in the moving product stream that need attention due to yield monitoring.
- Provide specific meat-to-product ratio for these recognized bone segments.
- Demonstrate the feasibility of simultaneous detection of certain low density foreign objects in the product steam, e.g., parts of plastic gloves, strings, rope etc.

An existing high-end vision hardware and software platform will be adapted and used for bone belt monitoring to deliver the target parameters mentioned above. The methodology and principles will be verified using relevant products sourced from the local industry and measured in lab testing sessions performed in the pilot plant at DMRI. The approach is to apply reference evaluation of collected image data with a scoring of boning work performance, i.e., 1-5, from well-cut to completely unacceptable. In a limited scale, the actual meat left on the bones will be weighed too for reference and bias adjustment.

The output of this project is a detailed design, implemented and pretested as a functional model, sufficient to:

- Demonstrate the working functionality of the concept(s) of Bone Belt Monitoring to AMPC staff.
- Develop indicative targeted $RRP.
- Draft a Stage 3 & 4 application for a developed and optimized unit for in-line testing in the EU or AU.

4.0 Methodology

The following activities and methods have been explored and accomplished during the entire project stage, separated into five Milestones.

M1. The measurement system based on Multispectral Vision Technology was modified and configured in preparation for the upcoming lab sessions in Milestone 2. The equipment was tested with a customized conveyor system imitating the existence of a bone belt.

M2. Two lab sessions were conducted within the pilot plant facility of DMRI, which allows handling of meat and bone products under food safety conditions and controlled temperature as close as feasible to normal appearance within in the industry. The bones from parts of lamb and cow were trimmed with different levels of meat still attached to the bones to test the measurement system in capturing image data of different kinds of bone segments. Furthermore, preliminary data analysis was initiated within this Milestone, and a visit to a local beef processor facility was also accomplished for fact finding and bone sourcing.

M3. Data collection in a larger scale was planned for this phase of the project to ensure sufficient image datasets of bones from beef for the upcoming data modelling phase in Milestone 4. Through dialog with the local processor industry, it was decided to source large boxes of bones, both trimmed and poorly trimmed, from two separate processor facilities for data collection at DMRI, instead of bringing the measurement equipment to a processor facility for either at- or inline data collection. The choice was made to reduce costs and risks, as well as any inconvenience, for the processors. The risk assessment of the impact of the rising corona situation in Denmark at the time was also conclusive for this decision. The data collection was accomplished in the pilot plant facility at DMRI and also included trimming sessions where meat was trimmed from the bone in different layers at a time with the recovered meat weighed between scans. Additional tests with low density foreign objects were conducted as well.

M4. Data analysis was conducted during this Milestone using different kinds of data modelling techniques including AI Deep Learning Neural Networks, which were used to train models for automatic recognition of the individual bone segment and prediction of the trim quality. Algorithms for foreign object detection and weight prediction were also developed.

M5. Final reporting was completed during the final Milestone phase of the project, including estimation of an indicative targeted $RRP and a proposal for the content on future project Stages, regarding a further developed measurement unit for in-line testing at an AU facility.

5.0 Project Outcomes

5.1 General Overview

In the following sections, the overall results from the entire project will be presented, mainly focusing on the specific outcomes from the data modelling phase of the project.

The outlines of the project results are divided into the following subjects:

- The development and refinement of the measurement system for Bone Belt Monitoring.
- Outcome of the procedures behind the trimming and yield tests performed at the pilot plant facility of DMRI.
- Results on the identification models for automatic recognition of different types of bone segments.
- Results on the estimation of the meat-to-product ratio.
- Results on the trim quality prediction according to the given Trim Score.
- Results on weight prediction of recoverable meat.
- Demonstration of the algorithms for foreign object detection.

5.2 The Measurement System

DMRI has developed and applied a Vision platform for this project, which is able to obtain image data through fast line-scan measuring. The general features of the Vision platform enable the system to be used in many versatile applications, where data collection and analysis of image data are necessary for monitoring different objects, such as meat and bone products on a processing line. The Vision system also proved to be robust within operations in the meat industry.

The camera sensor delivers image data comprised of 4 channels. Red, Green, and Blue (RGB) channels for visible light representation and a broader Near Infrared (NIR) spectrum, which represents the invisible light.

Figure 1. A Vision unit mounted above a conveyor line in a meat processing facility.

An existing Vision System unit was assembled and adapted for use in this project with a customized conveyor system applied for scanning bones on a test bone belt. Furthermore, software was refined to automatically collect full images of each bone segment when passing through the measurement system on the conveyor system.

Figure 2. Example of the scanning of a single loin bone (Lumbar Vertebrae) using the adapted Vision Measurement System (seen in front).

Figure 3. The corresponding captured image dataset of the loin bone: RGB image-part to the left, NIR image-part to the right.

5.3 Trimming and Yield Test

During the large data collection sessions performed at DMRI, a selection of very poorly trimmed bones was scanned in steps according to different trimming levels. The trimming levels or trim scores were defined and established through dialogue with yield and production experts, while the trimming sessions were performed by skilled trimming operators at DMRI. The specification of the 5-point scale, listed below, was chosen to apply for the different trimming levels defined as a trim score:

1. Optimal (ideal master trimmer level, no time pressure, no recoverable meat)
2. Accepted and nearly optimal (achievable at very focused deboning operations and very skilled and motivated operators)
3. Acceptable (average performance for variable trained and motivated operators)
4. Barely acceptable (only a few should occur, full focus on yield management and motivation)
5. Not acceptable, needs rework (may require a more skilled operator)

For yield testing, the recoverable trimmed-off meat was weighed in between each level of the defined trimming score.

Figure 4. Trimming operators working on different bones in steps to ensure corresponding data consisting of measurement scans and the registration of weight of recoverable meat for each of the five trim scores.

5.4 Identification Models for Automatic Recognition of Different Types of Bone Segments

The challenge of automatically identifying the specific bone segment moving along the conveyor system was achieved using modern AI Machine Learning tools such as Deep Learning Neural Networks (see for instance Farhadi et al.). The Neural Network can both locate and identify the bone of interest by "learning" the image representation of each bone segment. The overall performance of the neural network greatly depends on the provided input data, which must represent every conceivable variation of the bones.

Using an input dataset of approx. 6000 images, the network was trained to identify and locate the different types of bones on the conveyor system. A test set of 624 images, excluded from the input training set, were used to evaluate the performance of the classification, summarized in the *confusion matrix* below:

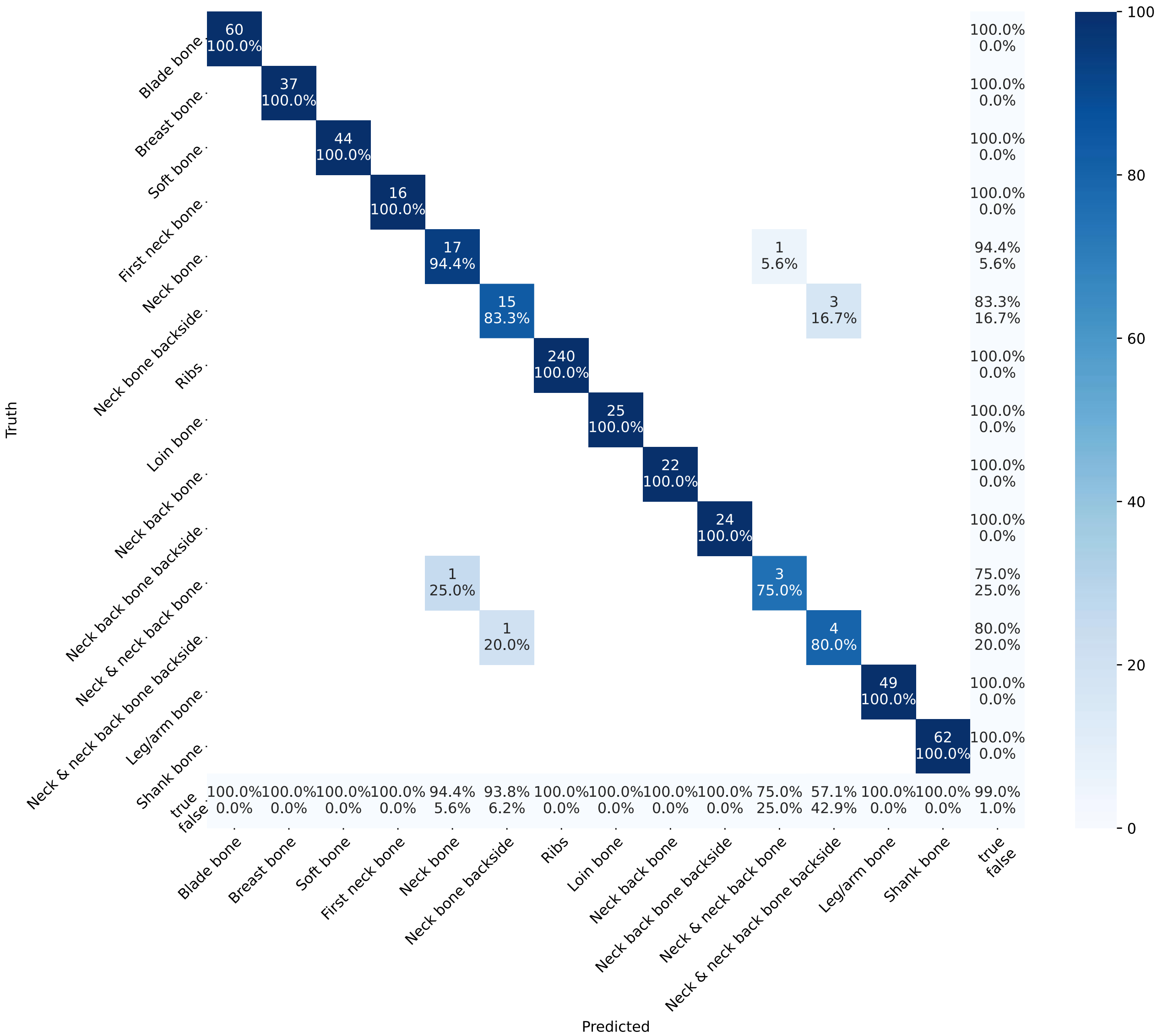


Figure 5. Confusion matrix for the identification results on different types of bone segments (see Bone Catalogue from the Appendix of the Milestone 4 report)

The confusion matrix highlights the correspondence between the predicted identification of a specific type of bone segment vs. the true ID reference. The matrix diagonal describes the number of correctly identified bone segments, while the off diagonal indicates bone segments that were incorrectly identified. As seen, 10 out of 14 bone types were predicted with 100% accuracy and for the remaining 4 bone segments, the mislabelled samples were identified as “neighbour” bone segments. Of the 624 images in the test dataset, only 6 images were mislabelled, which indicates a very high degree of prediction confidence.

Below is shown the actual output of the fully trained classification model, which both locates and identifies the specific bone segments as they pass the camera.

Figure 6. Example of two different types of bone segments located with a bounding box and identified with a score of certainty (from 0-1). The left bone segment is recognized as a blade bone (Scapula) and to the right, two ribs are identified and located correctly as well.

Overall, the results of the automatic segmentation and identification of several types of bone segments were very promising and made it possible to proceed to the next step in the analysis process.

5.5 Estimating the Meat-to-Product Ratio

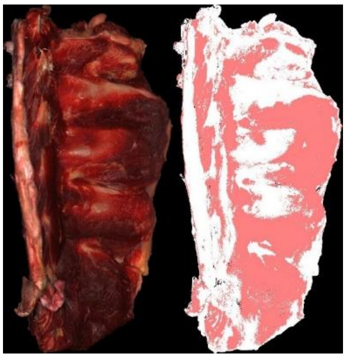
The segmentation algorithm between meat and product was constructed by training a specific machine learning model, a Random Forest classifier (see for instance K. Pykes), which classifies each pixel based on the pixel information, which consist of the standalone blue, green, red, and near-infrared intensities, but also the relations between them, such as blue/green, blue/red etc. In total up to 10 different features were extracted for each pixel.

The approach that was found most successful was to apply individual segmentation models for the various bone segments, since the colour characteristics of meat, fat and bone differ slightly between the different types of bone segments. The combination of the automatic identification models and the specific individual segmentation model for distinguishing bone from product is demonstrated below for a selection of bones at different trimming scores, evaluated by skilled trimming operators.

Trim score 5 | Trim score 1

Loin bone

Lumbar Vertebrae



Meat/Product ratio: 51%

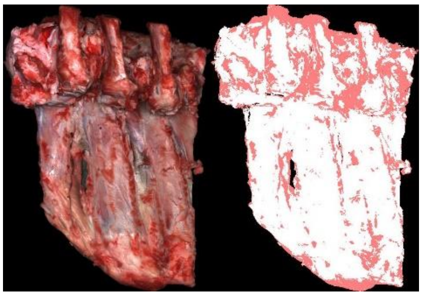
Meat/Product ratio: 10%

Neck back bone

Upper

Thoracic Vertebrae

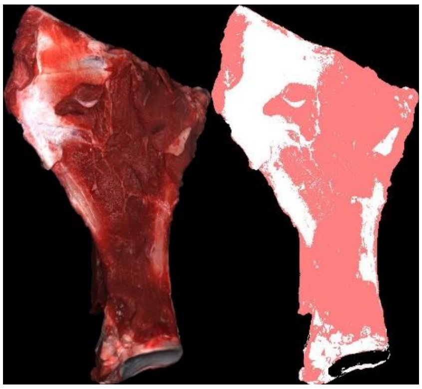
Meat/Product ratio: 79%



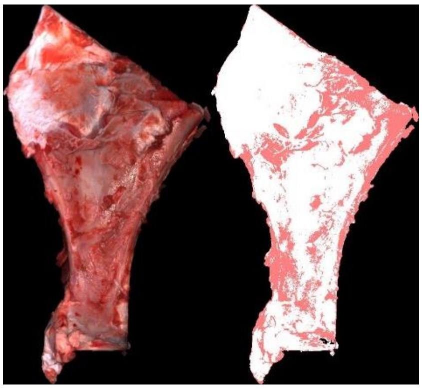
Meat/Product ratio: 27%

Blade bone

Scapula



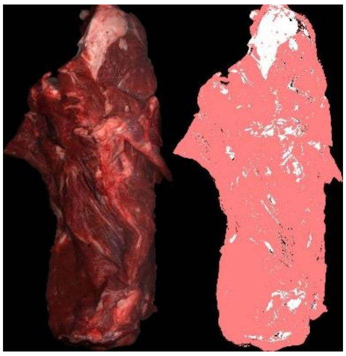
Meat/Product ratio: 64%



Meat/Product ratio: 28%

Neck bone

Cervical Vertebrae



Meat/Product ratio: 89%

Meat/Product ratio: 80%

Figure 7. Examples of different types of bone segments (for trim score level 1 (good) and 5 (poor)) and the result of the segmentation models into meat and bone. The false colour grading to the right is given by: Red = meat and White = bone. The meat-to-product ratio is estimated by the proportion of pixels belonging to meat vs. the entire product.

It shall be noted that there are certain areas with ambiguous visual representation that challenge the individual segmentation models. For instance, the areas containing a thin layer of red connective tissue (*periosteum*) attached to the bone surface are hard to categorise as either meat or bone product with a clear certainty.

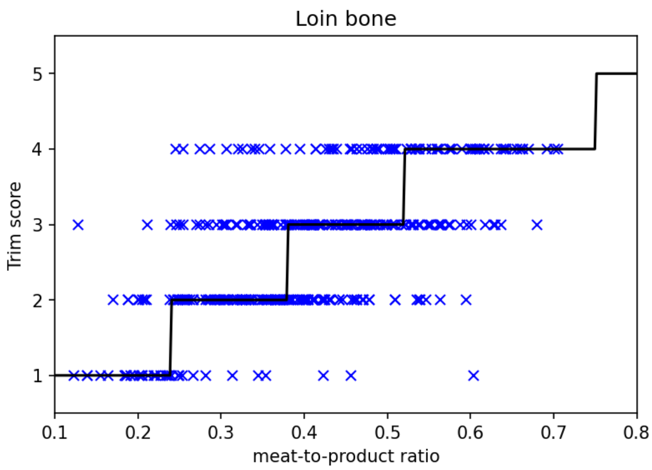
In general, the segmentation results for the meat-to-product ratio capture the differences between the levels of trimming quality, but for instance for the neck bone, the different thicknesses of the layers of meat are harder to distinguish, since the bone is never really exposed after trimming. Otherwise, the loin bone, neck back bone, and the scapula have bone surfaces that enables a trimming process, which leaves much less meat on the bone, and are therefore easier to separate.

5.6 Trim Quality Prediction

Prediction of the trim quality was investigated through different modelling experiments, all based on the selection of bone samples that were given a trim score by the trimming operators as outlined in section 5.3 (Trimming and yield test). In the following sections, the results of these experiments are summarized for two types of bones, the neck back bone (*Thoracic Vertebrae upper part*) and the loin bone (*Lumbar Vertebrae*).

5.6.1 Trim Score Prediction Based on Meat-to-Product Ratios

The correspondence between the meat-to-product ratio and the given trim score can be visualized in 2D plots for the existing datasets from the trim test performed at DMRI.



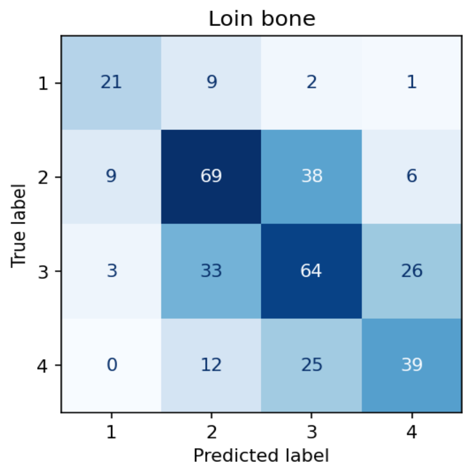
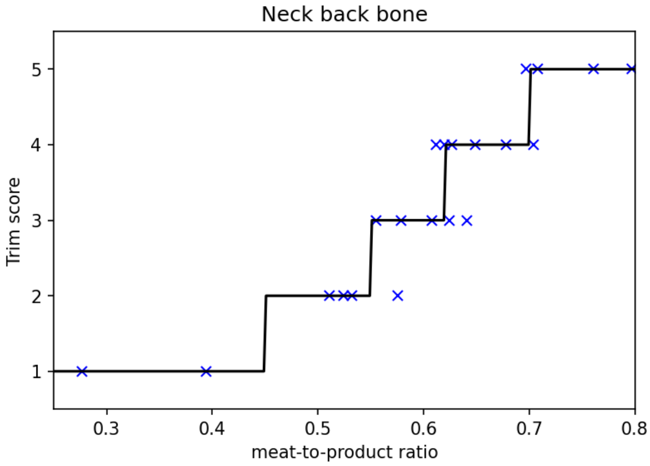


Figure 8. Plot of the meat-to-product ratio (1st axis) and the Trim Score (2nd axis). The trim scores from the loin bone are illustrated by blue crosses, with the manually constructed prediction model as the black line.

Confusion matrix for the trim score predictions with the manually constructed model.

For the loin bone, there is a large overlap of points from each trim score. Especially the three central levels are difficult to distinguish reflecting the physical similarity of these trim levels. Furthermore, the dataset does not span the entire 5-level trim scale. These problems make it difficult to train models by automatic means (e.g., multinomial logistic regression) that capture the underlying relationship (higher meat-to-product ratio equals higher trim score) with confidence. A more robust approach is to manually build a prediction model based on a visual inspection of the data. The model consists of a piecewise constant function where the steps are selected by hand to match the data as close as possible. The resulting model is shown as a black line. The model fits the data reasonably well, but unavoidably has points in the overlap regions that fall outside the model. However, most of these points do not differ by more than one level as illustrated by the corresponding confusion matrix.



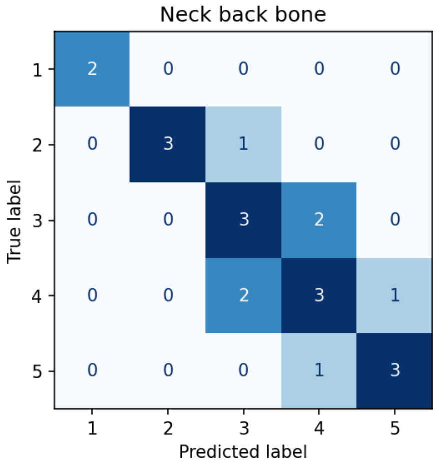


Figure 9. Trim scores from neck back bone (blue crosses) with the manually constructed model (black line)

Confusion matrix for the trim score predictions with the manually constructed model.

For the neck back bone, the same analysis steps were reproduced and showed a significantly more accurate modelling, even though overlapping between trim scores were still present, but much less obvious. The resulting confusion matrix also indicates a strong correlation for the prediction of the trim score based on the meat-to-product ratio.

5.6.2 Trim Score Prediction Based on the "Raw" Image Data

The approach to provide meat-to-product ratios for predicting the trim score is a reasonable method for highlighting the visual differences between trim scores, which was demonstrated in the previous section. The assumption that other information exists within the "raw" image data that can contribute to a better prediction model is plausible, since certain trimming procedures or techniques might be embedded within the image information, but not trivial to extract by common image segmentation analysis.

The use of classification modelling based on Deep Neural Networks was applied with the image datasets from a larger trimming test performed on loin bones. The results are given below, summarized by the confusion matrix listing the predictions for the excluded test dataset.

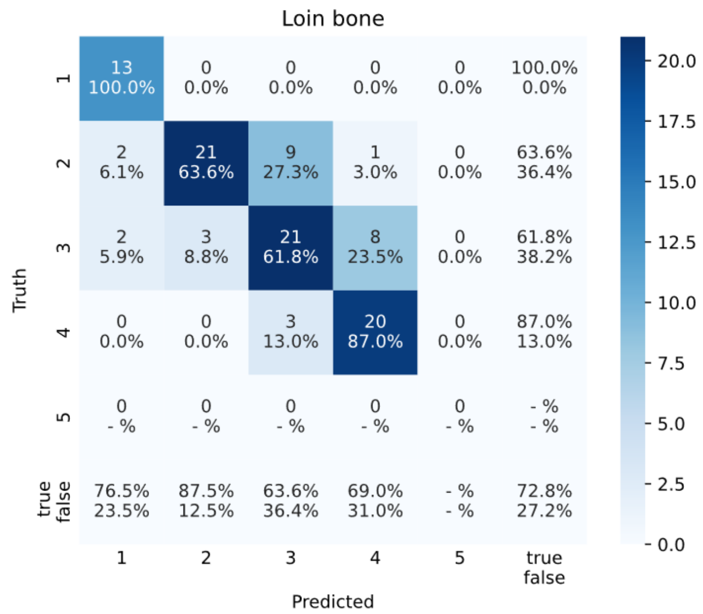


Figure 10. Confusion Matrix illustrating the performance of the prediction on the trim score of the loin bone.

The overall prediction looks quite good, with most of the incorrect predictions belonging to the closest trim score neighbour. A total of 72.8% correct predictions demonstrates a positive trend to utilize Deep Learning for trim score prediction.

5.6.3 Trim Score Prediction Based on Annotated Image Data

The trim score evaluations made during the lab tests at DMRI were performed visually by the trimming operators, who made the decision in 3D with the possibility of viewing the bone segment from different orientations. On the other hand, the applied Vision system only captures the bone sample from a single point-of-view in 2D. The differences might influence the performance of the classification model to correctly predict the trim score for all samples of a bone segment, e.g., the trimming level of a possible front and backside of a certain bone might look quite different.

This led to another approach, where the trimming operators assigned the trim score by using only vision image data based on what the camera had seen. For this purpose, an annotation software was written that showed each image in turn and presented the trimming operator with a choice of trim scores (1-5). This allowed for an efficient annotation of large datasets. The trimming operators disagreed in a significant number of cases, but most commonly, the difference was only ± 1 level, which can never be avoided due to the presence of borderline cases.

The annotated datasets containing images of the loin and neck back bone were used as 2 separate training sets for the Deep Learning Neural Network. The results of the test datasets for each of the two bone types are given below:

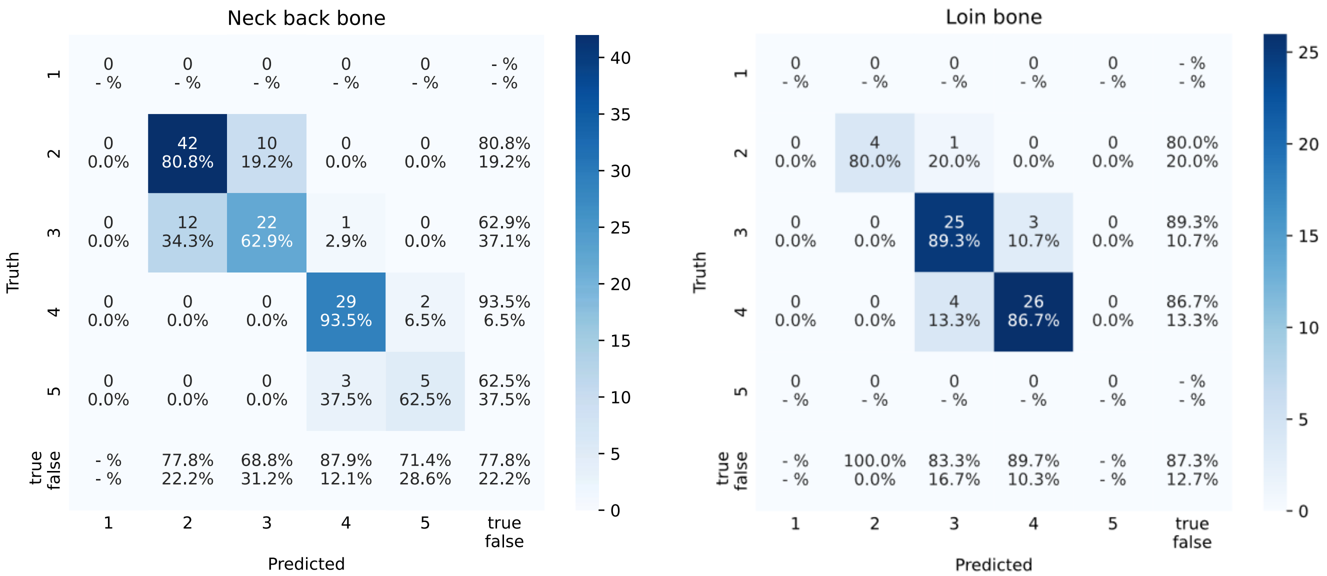


Figure 11. Confusion Matrixes summarizing the results of the Deep Learning Network approach to predict the trim score based on annotated image data.

The results on both the neck back bone and the loin bone look promising in terms of the overall prediction result of 77.8% and 87.3%, respectively, however, for the outer trim levels (1 and 5) insufficient data are available.

5.7 Weight Prediction of Recoverable Meat

From the trimming experiments performed at the pilot plant, weight data was recorded for a selection of bones to be used for prediction modelling of recoverable meat.

The total weight of the individual samples naturally varies with the size of each bone, giving a large spread in weight data. However, by assuming that for trim level 1 all recoverable meat has been removed, the weight data can be normalized to this “bare bone” weight. This has been done in the figure below, demonstrated for loin bones, where all samples have been assigned to zero grams of recoverable meat for trim level 1. The weight data is plotted against the meat-to-product ratio calculated for each image.

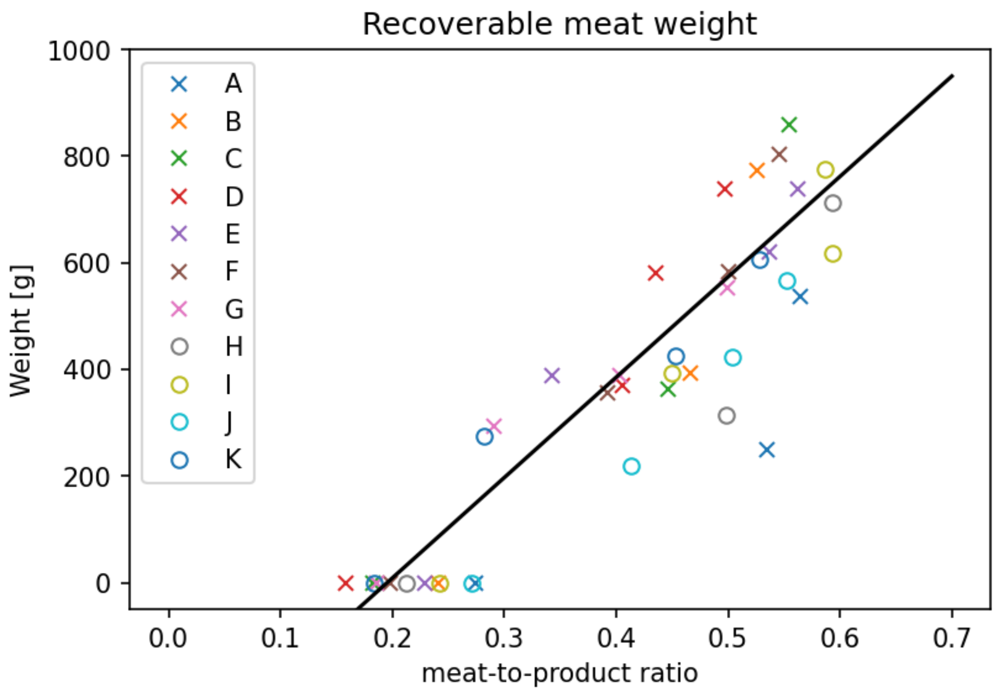


Figure 12. Weight of recoverable meat for 11 loin bone samples (A-K) plotted against the meat-to-product ratio from vision data. The black line is a linear regression through the training samples (crosses). Validation samples are shown as circles.

The samples have been split into a training set (crosses) and a validation set (circles). The training set was used to calculate a linear regression, which is shown as a black line. The validation set was used to check the validity of the regression model. As can be seen there is a clear and predictable relation between the meat-to-product ratio and the weight of the recoverable meat, which is well modelled by the linear regression (RMSEP of 118 grams for the validation set). The slope of the regression indicates an approximate 200 g of recoverable meat per trim level.

The model provides an indication of the amount of recoverable meat and thereby the value that is lost at the bone belt.

5.8 Foreign Object Detection

The Vision system is also designed to detect many types of coloured foreign objects including low density plastic, robe, or strings down to a few millimetres in size and at a very fast pace, up to 1 meter per second. When bones are used for further processing for human or petfood consumption, this is as important as for meat cuts and trims, e.g., beef stock and other bone side stream products.

To demonstrate the capability of foreign object detection, the different test samples of bones were processed by the detection algorithms with the addition of separating the green background of the conveyor belt, which was used in the current Vision setup. The result of the foreign object detection is demonstrated below:

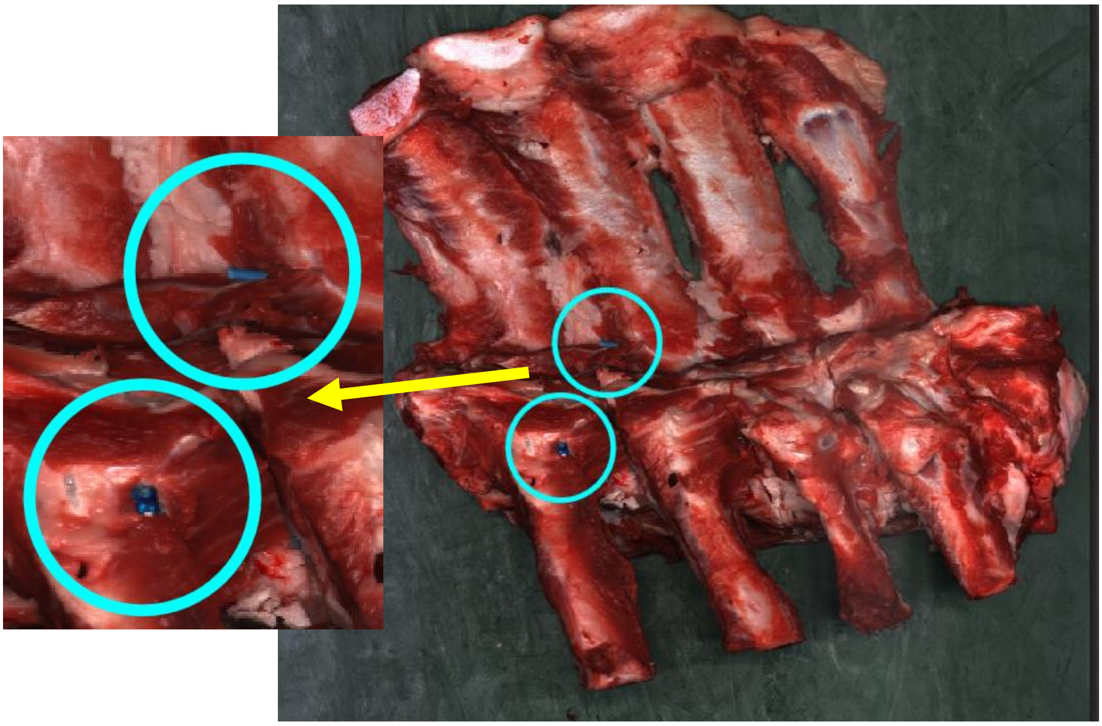


Figure 13. Example of two small pieces of robe/string in the product (the piece of blue wire is 2.7 mm long), testing the foreign object detection algorithm.

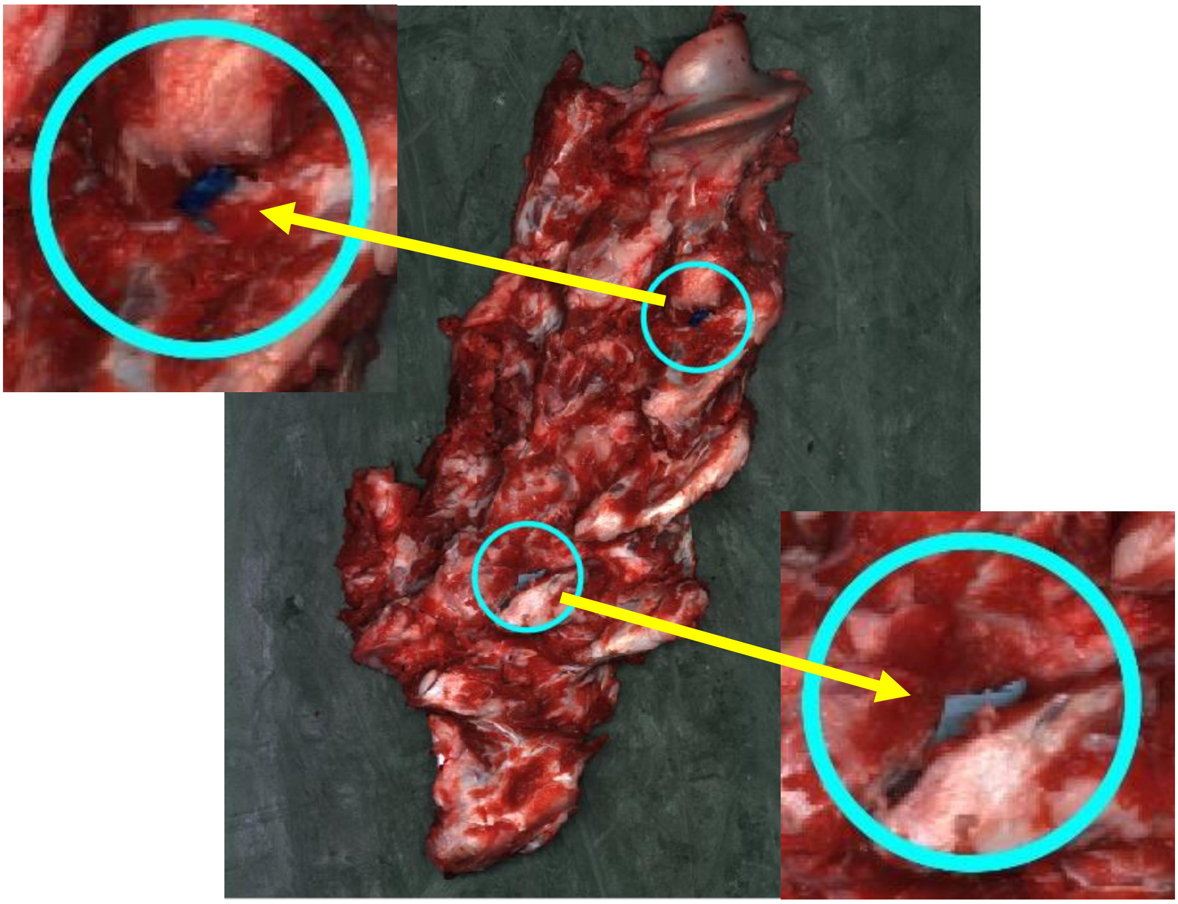


Figure 14. Example of two small pieces of plastic with different nuances of blue.

6.0 Discussion

The activities of the project have been focused on establishing a measurement system for bone belt monitoring including development and refinement of both hardware and software. The modelling effort focused on bone segment identification, prediction of the trim quality, and the estimation of recoverable meat.

Bone segment identification models were developed using state-of-the-art machine learning techniques. The resulting models were able to correctly identify all bone segments with a very high confidence. The few incorrectly labelled samples typically fell into the closest neighbouring categories.

The models were trained on images of isolated, non-overlapping bones and therefore fail for overlapping bones, which may appear at processing facilities with a bone belt. In practice and to a large extent, this can be remedied by mechanically separating the bones on the bone belt, so as many bones as possible are presented individually. It is most likely not necessary to analyse all overlapping bones in a given pile to achieve valid yield performance KPI’s on a continuous running belt monitoring installation, as sufficient samples can give a good indication of the general trim level of the production.

Another approach is to retrain the identification models with overlapping bone samples (for instance images from a real-world processing facility), giving the models the ability to pick out individual bones from a pile. This type of multinomial classification is more advanced and requires further development and a much larger training dataset, ideally from inline data collection, but is expected to be a very feasible approach.

The meat-to-product ratio was estimated based on the pixel RGB+NIR values of the 2D image. White pixels were classified as bone while deep red pixels were identified as meat. The pale red areas in between, mainly consisting of red connective tissue, made the segmentation a bit more difficult for certain types of bones. Overall, the outcome of the segmentation for the meat-to-product ratio did capture the clear differences between the levels of trimming quality with reliable results.

Trim quality was predicted as well using the results from the segmentation of meat vs. product. It was found that most of the examined bone segments followed the basic trend that higher meat-to-product ratio implied worse trim quality. However, some overlap between the trim levels was also evident, especially for the central three trim levels.

There can be several reasons for the general level of overlap. Firstly, borderline cases always exist, where trimming operators assign different trim scores. Secondly, for 2D image data only half the bone is visible, which can hide (or show) chunks of meat that could tip the trim score to either side. Thirdly, given physical access to the bone, an expert operator would typically turn the bone over and inspect it from more angles to better see the full product, textures, and shadows, which help in assessment. This extra information is not available on 2D image data. The possibility of applying a two-side measurement system with a customized waterfall bone belt will contribute to more image information.

Applying Deep Learning Networks for trim quality prediction. A similar picture is evident for the use of “raw” image data, where the neural network algorithm is allowed to autonomously choose image features that contribute to the best prediction of the trim score. The chosen features are embedded within the network and cannot be directly interpreted, hence the network acts as a black box. The strength of the neural network approach is the ability to learn certain “hidden” features within the image data, such as recurrent patterns in trimming techniques, which can be extracted from the image data and contribute to a better prediction of the trim score. For the neural network approach, 1-off-diagonal predictions between trimming scores also occur, but not as significant as for the segmentation analysis model, which verifies the evidence of hidden features within the entire “raw” image.

In a production setting, the trim score of the individual bone is of less interest than the development in the average trim score over time (say, a few hours). By monitoring the continuous average trim quality by a constant unbiased method, the level of overlap and outliers in the data becomes less important, and the underlying relationship is recovered (higher meat-to-product ratio equals higher trim score). With this in mind, it is expected that the models are sufficiently accurate for monitoring the recoverable meat level/trim quality as a KPI over time periods, to use it as a valuable optimisation tool, and that the accuracy can be improved with more training data.

7.0 Conclusions / Recommendations

The work from M1 to M4 has demonstrated that it is possible to use an industrial Vision platform to retrieve image data based on an RGB+NIR camera sensor. By developing analytic software on captured data, the solution provides parameters that correlate to potentially recoverable meat on bone, both as assessed by a visual appraisal and by actual weights.

During the project, data have been collected in a production-like environment with a robust equipment platform that was proven in the industry and has been used at many international food production locations since 2016 with a minimum of service & maintenance issues. Hence, there appears to be no limitations in installing the equipment for Australian Bone Belt applications with full in-line use and a fine-tuned user interface that will allow harvesting of full value from yield parameters, by corrective actions, even at individual bone segment level.

Monitoring the bone belt continuously allows a 1:1 evaluation of all identifiable bone segments that would offer significant additional value to the cutting floor manager’s sample control on the work from the boning room. For a given batch type, the overall performance can be monitored, while at bone segment level the (recoverable) meat-to-product ratio can be estimated. This enables target re-evaluation and ensures that corrective actions can be implemented to improve the yield in the boning room. Furthermore, for the processors using the bone products for further processing into human or petfood applications, it can be validated that unwanted foreign objects are detected and can be flagged for removal.

The technology investment for establishing a final complete system on the boning line is considered medium high, in the range of 150-185.000A$ RRP (estimated by 2022 price level), including commissioning. Pricing will also depend on: final specification, time of supply, and whether it is: single- or multiple-build, supply- & installation cases.

The business case and payback time for the individual processor will depend on many factors, e.g., the current level of performance in the boning room, the price of beef, production volume, the carcasses processed, and not least how well the users are able to use the data for a continuous improvement of the operation, by correction and training instructions etc. From previous experience in pork deboning operations, and through many optimization & yield boost projects, it has been observed that with an increased focus, instructions and training, a potential in the level of 1-3 mill A$ yearly can be realized for processers by more attention and training. Thus, with the current high Beef prices, the potential could be significant.

With the feedback of data on KPI’s from this solution, it is considered feasible changing the boning room performance for many processors by harvesting an additional 500 g of meat product on average, from the full bone segments of each carcass. In this case, the payback time for the investment would be in the order of approx. 3-6 months depending on production volume. Considering that for most bone segments, each step up in boning quality on the applied 5-point scale was in the range of 50-500 grammes of additionally harvested meat, per bone segment, depending on the bone product. With this in mind, it seems feasible to achieve the above target, also without a significant impact on processing time, which will change the business case for the investment. Such a move is also well in alignment with the global agenda of making more with less, and producing less waste, which will be the case, especially if the bone stream is not for human or petfood usage.

In the subsequent project Stages, it is recommended to build and install an in-line equipment at an AU processor facility to further develop and test the solution from a continuous product stream. The measurement system must run for an extended period for fine tuning and validation of the estimated KPI's, along with some sample verifications of individual bone segments by actual weight of recoverable meat, for necessary bias adjustment at bone level.

An optimal HMI with the presentation of selected KPI dashboard parameters is to be designed and developed. Furthermore, the exchange of data features to relevant data systems at the processor site will be examined. Through a validation process, the ability for in-line estimation of the potential recoverable meat will be determined, and the potential actions for improving boning yields will be documented as a start to demonstrate the payback of the solution.

8.0 Bibliography

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