Final Report

Bone Belt Monitoring

Bone Belt Monitoring – Vision combined with DEXA Stage 2

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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 in combination with a dual energy x-ray unit for monitoring the product stream of a Bone Belt by developing algorithms capable of determining the trim quality of 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 equipment consists of a multispectral (RGB and NIR) vision system in combination with a DEXA x-ray unit. The data from the two sensor systems complement each other, as the vision data provide information of the visual appearance of the product surface while the x-ray unit gives access to thickness information.

The equipment and recording software were prepared and tested in a series of short laboratory sessions on bones from lamb and cattle at the pilot plant facility at DMRI. During these sessions, the general procedures to be used in subsequent larger data collection sessions were developed, and the definition of a 5-level trim score scale for describing and discussing trim quality was settled.

Large boxes of both well-trimmed and poorly trimmed bones from cattle were sourced from two local processors for large scale data collection at the DMRI pilot plant facility. All bones of an appropriate size (equipment opening was W40xH12 cm) were scanned by the equipment in all natural orientations, and a subset of bones was selected for specialized trimming and yield experiments. In these experiments, each bone was trimmed in steps by skilled trimming operators to produce progressively better trim quality. At each trim level, the bone was weighted and scanned by the equipment. The collected datasets formed the basis of the subsequent algorithm development effort.

Additionally, separate experiments were performed to demonstrate the foreign object detection capabilities of the vision system. Several low-density objects of varying sizes and textures 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 methods, such as deep learning neural networks, were employed for bone segment classification, as correct classification enables better yield estimate models. The classification models were able to correctly identify all 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.

The trim quality is directly linked to the amount of recoverable meat left on bones. Therefore, models for estimating the meat-to-product ratio were first developed for vision and x-ray data and then related to the trim score assigned by experienced trimming operators. It was found that both technologies were capable of predicting the trend in trim quality for a range of bone segments, while predictions for individual bones were associated with some uncertainty. It was also found that combining data from vision and x-ray resulted in more robust and reliable models.

Monitoring the bone belt continuously allows for a 1:1 evaluation of all identifiable bone segments and would therefore offer a significant additional value to the cutting floor manager's sample control of the boning room work. 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 reevaluation and ensures that corrective actions can be implemented to improve the yield in the boning room. Furthermore, for the processors using the products for further processing for 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, including the current level of performance in the boning room, the price of beef, production volume, the carcasses processed, and certainly how well the users are able to utilize the data for a continuous improvement of the operation, by training instructions etc. From pork deboning operations, it has been observed (through many optimization/yield boost projects) that increased focus, instruction and training can potentially result in a yearly benefit in the level of 1-3 million $ at the processors. With the current high beef prices, the potential could therefore be significant.

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. 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.

As the DEXA technology comes at both a higher CAPEX and OPEX, it is relevant to balance whether the proven minor increase in precision of the recoverable meat to be harvested can justify the increased complexity and cost over a simpler vision solution.

In the AMPC and industry context, it is recommended to start out at an Australian processor's bone belt with focus on validating how much of the potential that can be harvested by a vision set up alone. If the potential and value creation is very significant, the next likely step could be to explore either a 2 or 3 side free fall/waterfall vision solution compared with a combined DEXA and RGB+NIR solution.

2.0 Introduction

The goal of this Stage 2 project within Bone Belt Monitoring is to adapt and refine an existing high-end vision and x-ray system for monitoring the product stream from a bone belt and to develop algorithms capable of determining the trim quality as indicated by the amount of meat still attached to the bones. The monitoring system will enable the meat processor to react to changes in yield performance and identify operation problems early 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 a lab test in the pilot plant at DMRI and secondly at a large scale with bones collected from a processor.
- 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 plastic 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 from 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 are to 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 at the EU or AU.

4.0 Methodology

Through the five Milestone phases of the project, the following activities and methods have been explored and accomplished:

M1. The measurement system based on combined multispectral vision (RGB+NIR) and dual energy x-ray (DEXA) 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 an operating bone belt.

M2. Two lab sessions were conducted within the pilot plant facility at DMRI where meat and bone products could be handled under food safety and temperature conditions similar to those at a typical abattoir. Selected bones from lamb and cattle were trimmed to different trim quality levels and then scanned to test the measurement system on different bone segments. Preliminary data analysis was initiated within this Milestone, and a visit to a local beef processor facility was also accomplished.

M3. Large scale data collection was carried out in this phase of the project to ensure sufficient image datasets of cattle bones for the upcoming data modelling phase of Milestone 4. Through dialog with the local processor industry, it was decided to source big boxes of bones, both trimmed and untrimmed, 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 worsening COVID-19 situation in Denmark at the time also contributed to this decision. The data collection was accomplished in the pilot plant facility at DMRI and included trimming sessions, where bones were trimmed to different trim qualities and the recovered meat was weighted between the scans. Additional tests with low density foreign objects were conducted as well. Furthermore, a series of CT scans were performed to produce reference thicknesses for bone and soft tissue.

M4. Data analysis was conducted during this Milestone using different kinds of data modelling techniques including AI Deep Learning Neural Networks, which were used for training models for automatic recognition of the bone segment and prediction of the trim level. 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 a future Stage 3 + 4, regarding a further developed measurement unit for in-line testing at an AU facility.

5.0 Project Outcomes

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

The outcomes of the project are divided into the following areas:

- Development and refinement of the measurement system for bone belt monitoring.
- Trimming and yield tests performed in the pilot plant facility at DMRI.
- Identification models for automatic recognition of different types of bone segments.
- Trim quality prediction.
- Weight prediction of recoverable meat.
- Demonstration of the algorithm for foreign object detection.

5.1 Measurement System

DMRI has developed a high-end vision platform that consists of a multispectral camera system able to obtain image data through a line-scan measuring technique. The general features of the platform enable the system to be used in many versatile applications, where data collection and analysis of image data are necessary for monitoring objects on a processing line.

Figure 1. The test unit combining vision and x-ray technology mounted with a moving conveyor with a green belt.

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.

For this project, a test unit (see Figure 1) was modified for a combined system with both vision and x-ray sensors in the same cabinet to explore how the two technologies could contribute to a joint solution. The chosen x-ray technology is based on Dual-Energy X-ray Absorptiometry (DEXA), which means that each measurement records the attenuation of x-rays at two different energy levels. The x-ray image data therefore consist of two channels, one for each energy level.

Both the vision and x-ray systems are capable of measuring moving objects through line-scanning, i.e., scanning a continuous stream of meat and bone products moving along a conveyor belt. This feature enables the experiments within the project to imitate a true production line at a food processing facility.

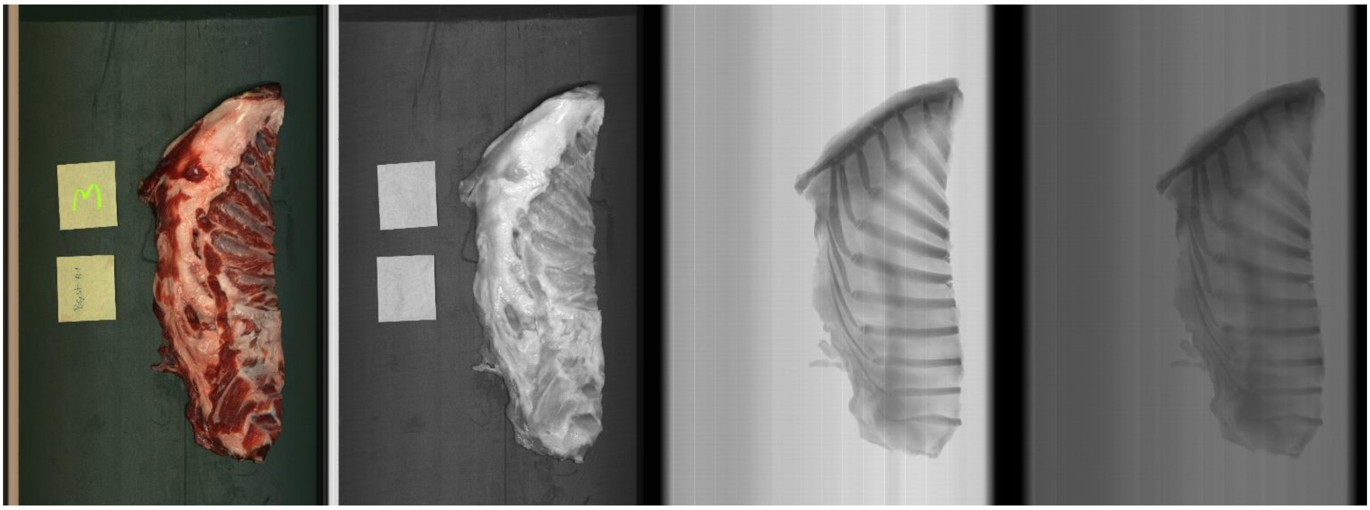

Figure 2. Example of image data from combined RGB+NIR and DEXA unit. From left to right: RGB, NIR, low energy x-ray and high energy x-ray.

5.2 Trimming and Yield Test

During the large data collection sessions performed at DMRI, a selection of poorly trimmed bones was processed. Each bone was trimmed to a certain trim level and scanned on the measurement system, going from the initial (poor) trim level to progressively better trim levels. The trimming levels (or trim scores) were 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-level scale below was chosen to apply for the different trimming levels/scores:

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 recovered meat was weighed between each level of the defined trimming score.

Figure 3. Trimming operators at work in the trimming and yield test. Weight measurements and scans were secured for each of the five trim levels.

5.3 Bone Segment Identification

Automatic identification of specific bone segments moving along the conveyor system was achieved using modern AI Machine Learning tools, specifically Deep Learning Neural Networks (see for instance Farhadi et al.). The Neural Network is able to both locate and identify the bone of interest by learning to recognize the image representation of each bone segment. The overall performance of the neural network greatly depends on the provided input data, which need to be adequate for representing every conceivable variation of the bones.

Using an input dataset of approx. 6000 images, the network was trained on vision data alone 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 in Figure 4:

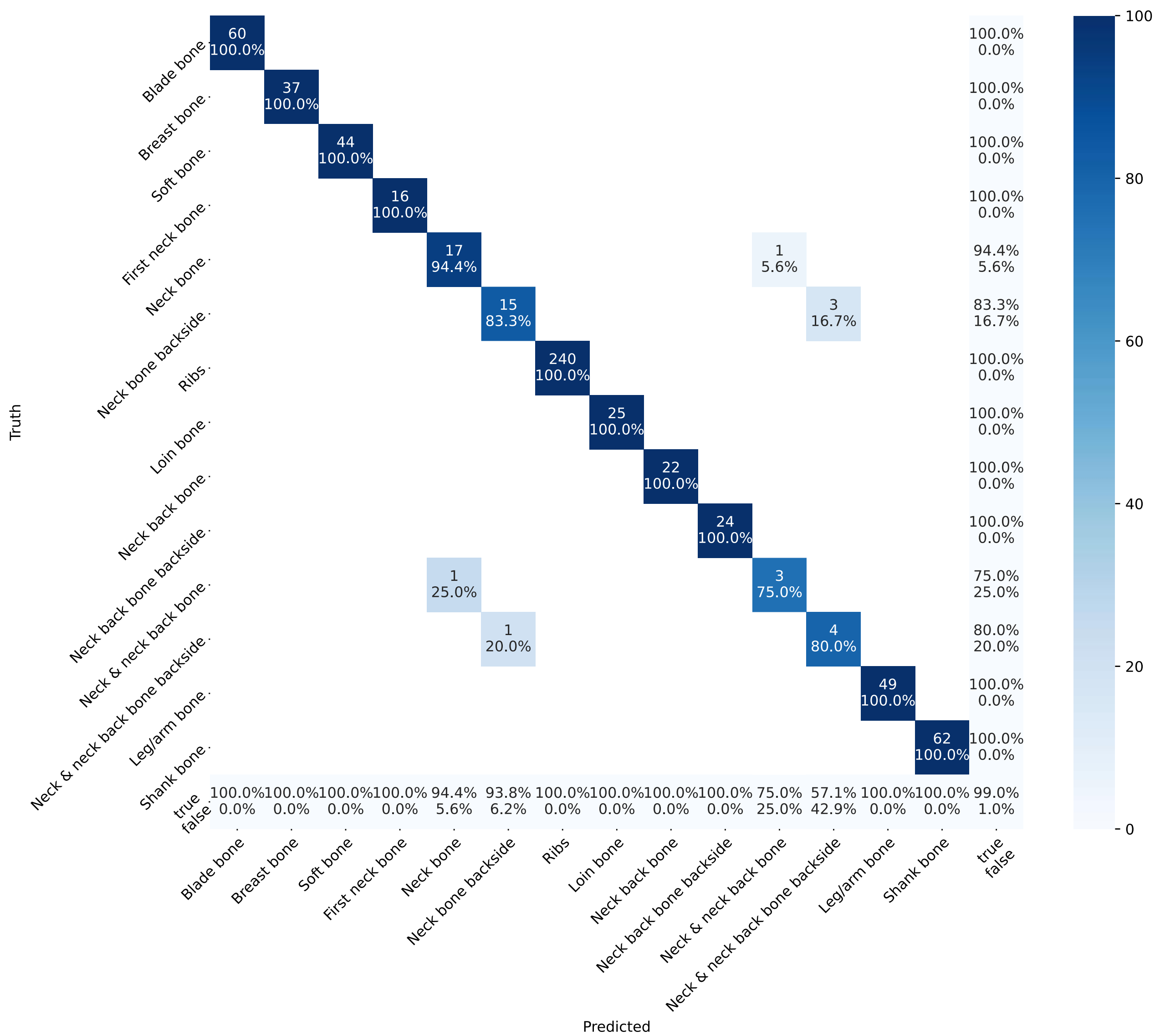

Figure 4. Confusion matrix for the identification results on different types of bone segments (see bone segment catalogue in Milestone 4, appendix).

The confusion matrix highlights the correspondence between the predicted identification of a specific type of bone segment vs. the true type. The matrix diagonal indicates the number of correctly identified bone segments, while the off-diagonals indicate 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.

Figure 5 shows the actual output of the fully trained classification model, which both locates and identifies the specific bone segments as they pass the camera.

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.

Figure 5. 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 localized correctly as well.

5.4 Trim Quality Prediction

The trim quality is directly related to the amount of meat left on the bone, and therefore a good estimate of the meat-to-product[1] ratio enables prediction of the trim quality. Robust models for soft and bone tissue segmentation were developed separately for the RGB+NIR and DEXA data, and the trim score from the trimming tests were used to describe the trim quality.

For RGB+NIR, a specific machine learning model (a Random Forest classifier, see for instance K. Pykes) was trained, which classified each pixel based on the colour 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, 10 different features were extracted for each pixel. The model correctly identified areas with red meat and white bone, but had trouble identifying thin layers of meat, fat, cartilage, and reddish bone. Furthermore, the meat and bone presentation varied across different bone segments, and it was necessary to tailor the segmentation models for specific bone segments to get reliable results.

Segmentation was found to work best for bone segments where the bone surfaces were clearly visible and had a colour nuance that was distinctly different from meat. Loin bones (*lumbar vertebrae*) and neck back bones (*thoracic vertebrae*) were found to be well suited for this type of analysis while, for instance, the neck bone (*cervical vertebrae*) did not present any visible bone, which made segmentation more difficult.

[1] In practice, it is difficult to distinguish between meat and other forms of soft tissue. In the rest of this report, soft tissue and meat are used interchangeably.

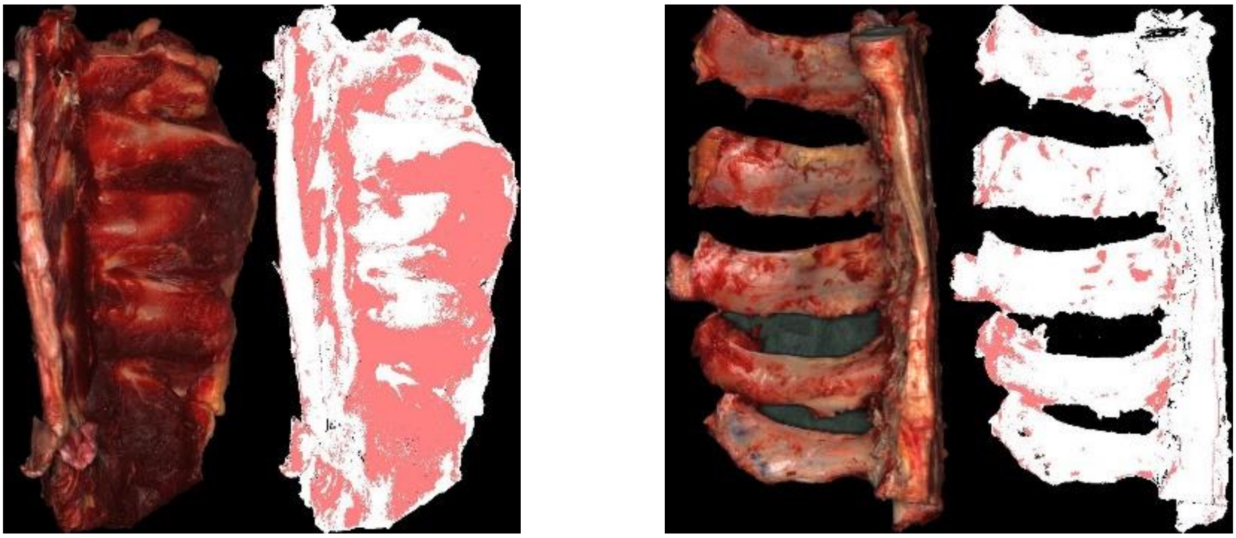

Figure 6. Meat and bone segmentation for a loin bone (*lumbar vertebrae*) using RGB+NIR data. The estimated meat-to-product ratios are area-based. Left: Trim quality 5 (meat-to-product = 51%). Right: Trim quality 1 (meat-to-product = 10%).

For DEXA, the segmentation was achieved through a combination of specialized DEXA methods and machine learning models that were trained on reference data material from CT scanners at DMRI. It was found that the presence of bone would invalidate the prediction of soft tissue thickness so that only soft tissue on the bone edges contributed to the meat-to-product ratio. Therefore, the ratio was more accurate for bone segments that exposed soft tissue outside the bone structure, e.g., loin bone and neck back bone, and less accurate for bone segments where most of the soft tissue was naturally obscured, e.g., blade bone (*scapula*). Cartilage was found to be difficult to distinguish from meat and therefore contributed to the meat-to-product ratio with a bias that depended on the bone segment.

$$f_s = 32.5\ \%$$

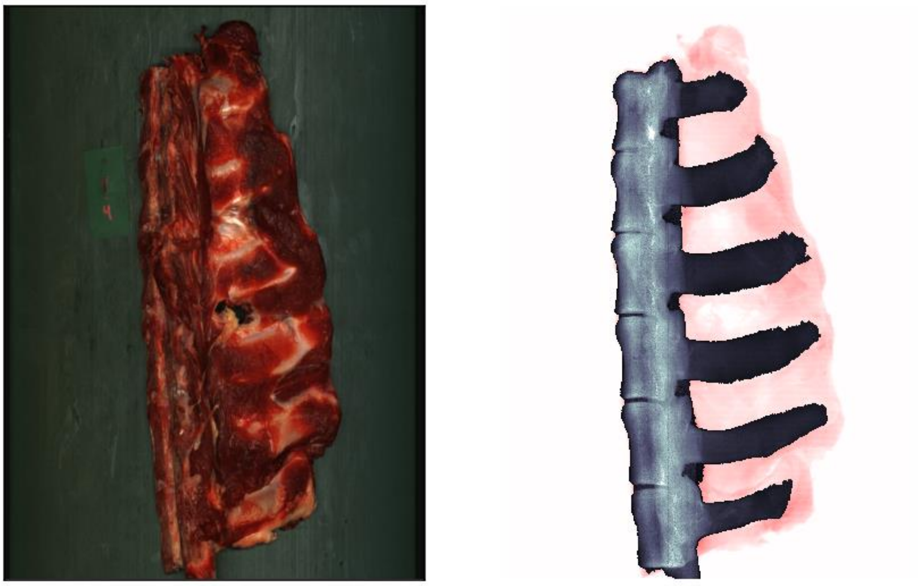

Figure 7. Meat and bone segmentation for a loin bone using DEXA data. The estimated meat-to-product ratio (here 32.5%) is volume-based. Cartilage at the bone edges is grouped with meat.

Based on the meat-to-product estimate performance, the loin bone and neck back bone were selected for further study. The results from both bone segments were similar, and in the following only data from the loin bone are presented.

Using the meat-to-product estimates from RGB+NIR and x-ray, the trim quality (i.e., the trim scores from the trimming tests) was predicted both separately for the two technologies as well as in combination. The prediction models captured the general trend in the data very well, although a significant overlap between the individual trim levels was evident.

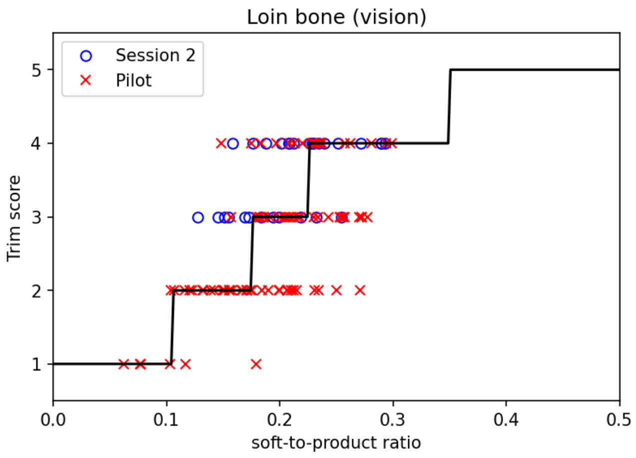

Figure 8. Predicted trim quality for loin bones using RGB+NIR data. There is a significant overlap between the trim levels.

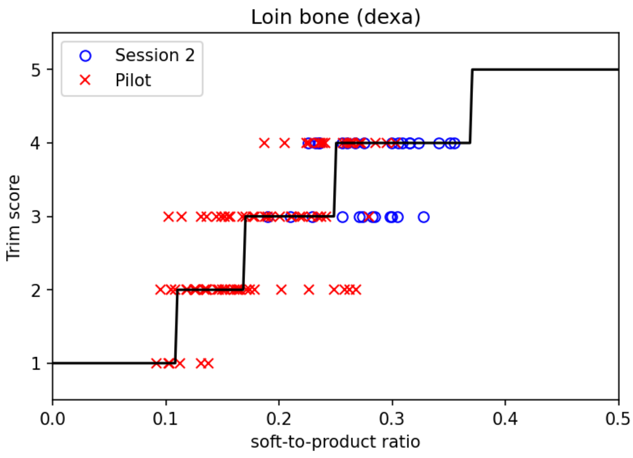

Figure 9. Predicted trim quality for loin bones using DEXA data. The level overlap is slightly reduced, and the general trend is seen more clearly.

In part, the level overlap is due to inaccuracies in the reference trim score as assigning consistent trim scores is difficult even for experienced operators. Another contributing factor is the limitations of the individual technologies. RGB+NIR only sees surface meat on one side of the bone and cannot estimate the thickness of the layer. DEXA can estimate meat thicknesses, but only where it is not blocked by bones.

It was found that the level overlap could be reduced by combining data from both technologies. The meat-to-product estimates from RGB+NIR and DEXA were mean averaged and used as input to the trim quality prediction model. This yielded a single model that was able to predict the trim quality of individual bones with fair confidence (see Figure 10). The corresponding confusion matrix (Figure 11) shows that most data points fall in the diagonal (exact prediction), while a smaller number is off by one level. Approximately 70% of the samples were correctly predicted using the combined RGB+NIR and DEXA dataset, while for the two technologies alone the number was in the range of 55-60%.

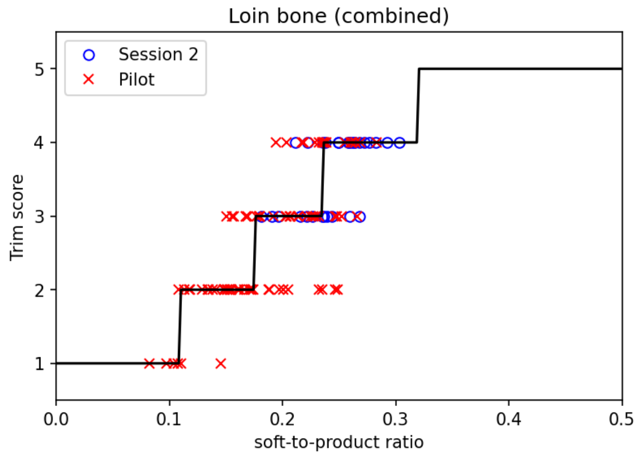

Figure 10. Predicted trim quality for loin bones using combined RGB+NIR and DEXA data. The level overlap was reduced compared to the individual technologies.

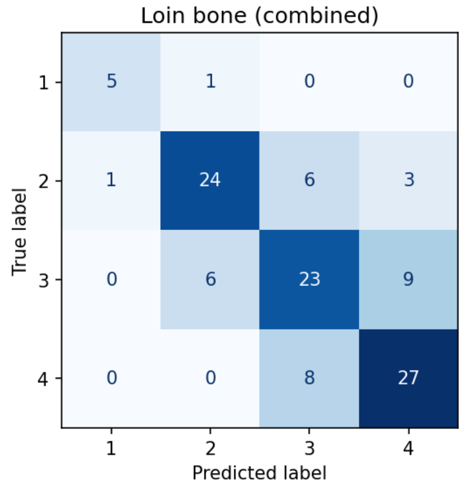

Figure 11. Confusion matrix for the combined model. “True label” is the trim score from trimming experiments while “Predicted label” is the predicted score. The cells indicate the number of samples. The diagonal represents exact predictions. The diagonal +/- 1 represents off-by-one errors, etc.

The RGB+NIR and DEXA meat-to-bone estimates are based on different data. The RGB+NIR quantity is based on area data, while the DEXA quantity is volume based and therefore captures different aspects of the meat and bone, which accounts for the increase in model accuracy.

The combined model is considered accurate enough to be used for prediction of trim scores of individual bones. For the purpose of monitoring the trim quality trend across longer time/several samples, the model from each technology alone is expected to suffice.

5.5 Weight Prediction of Recoverable Meat

During the trimming experiments at the pilot plant, weight data was also recorded for a selection of bones. The total starting weight of each bone was first noted and then for each trim level, the amount of recovered meat was weighed as well. By using the same techniques as in section 5.4, a prediction model for recoverable meat was constructed. Here, we focused on the loin bone as the bone segment with the most samples. However, many of the samples were too large to fit through the combined RGB-NIR DEXA equipment opening, and we therefore only used the vision data, which was available for all samples.

Naturally, the total weight of the samples varies with the size of each bone, giving a large spread in the weight data. However, by assuming that for trim level 1 all *recoverable* meat has been removed, the weight data can be normalized to this “clean bone” weight. This has been done in Figure 12 for loin bone where all samples therefore have zero grams of recoverable meat for trim level 1. The weight data is plotted against the meat-to-product ratio calculated for each image.

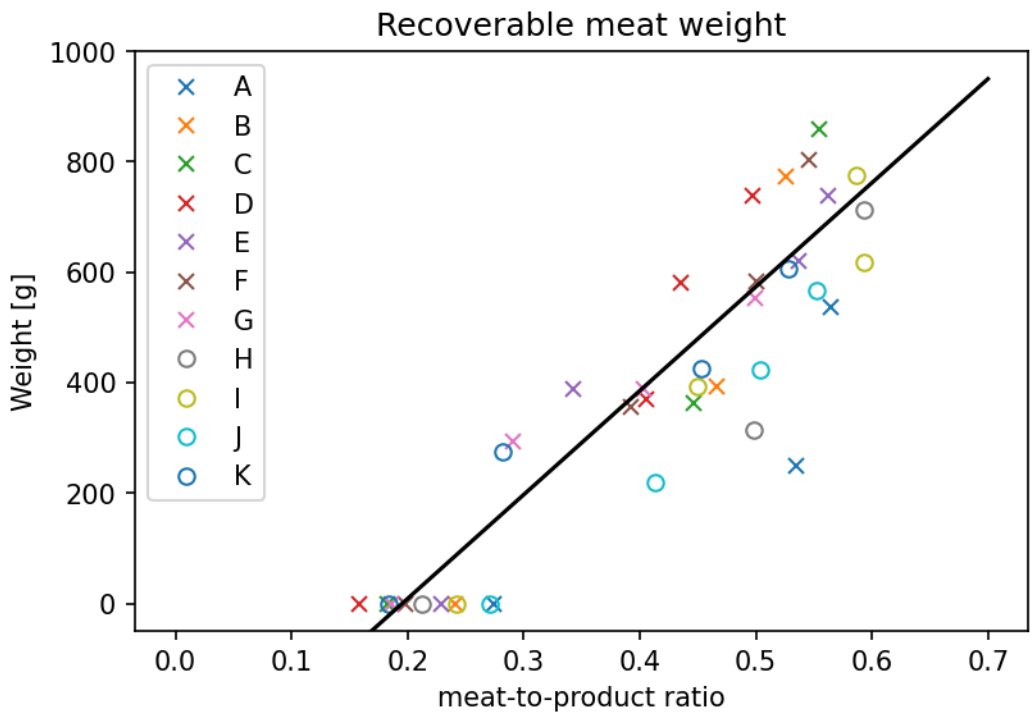

Figure 12. Weight of recoverable meat for 11 loin bone samples (A-K) plotted against meat-to-product ratio from vision data. The black line is a linear regression through the training samples (crosses). Validation samples are shown as circles.

The samples were 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 g for the validation set). The slope of the regression line indicates an approximate 200 g of recoverable meat per trim level. The spread of the trim level 1 points is due to two factors. First, normal trimming methods will always leave a little meat on the bone, so that the level 1 points should not really be zero. Second, any meat left on the bone will be interpreted by the meat-to-product estimation models as a non-zero meat-to-product ratio giving an uncertainty in the position on the x-axis.

The model gives an indication of the amount of recoverable meat that is lost at the bone belt based on vision data alone.

5.6 Demonstration of Foreign Object Detection

The vision system is designed to also 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 in Figure 13.

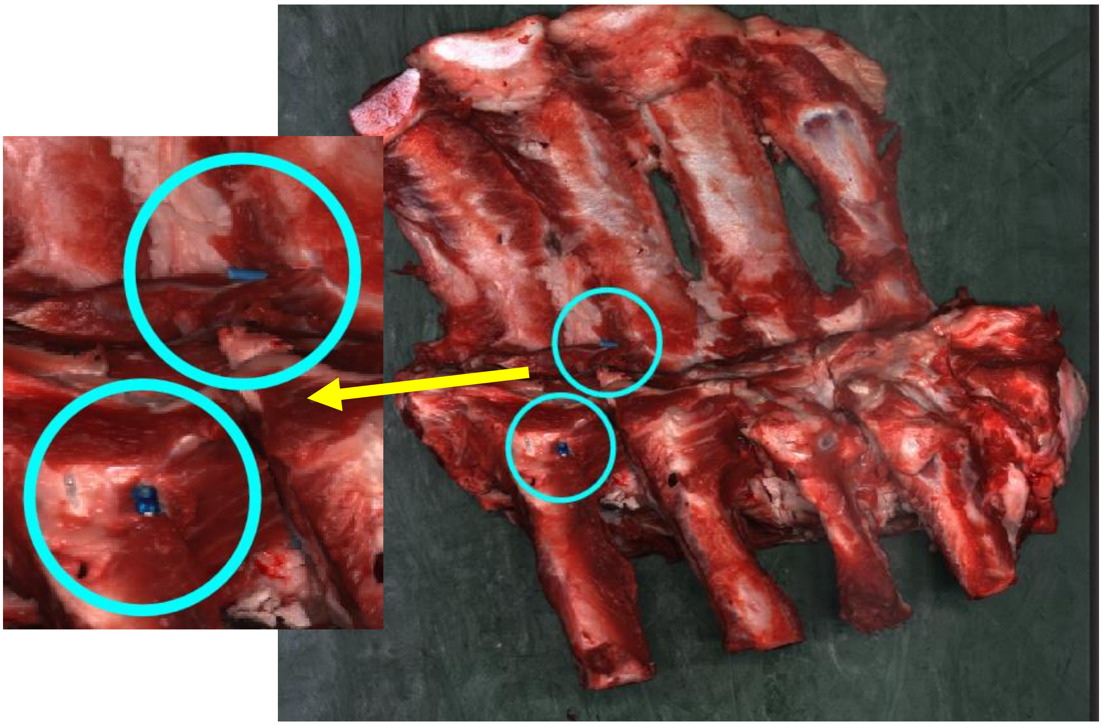

Figure 13. Example of two small pieces of robe/string in the product (the piece of blue wire is 2.7 mm long), testing the foreign object detection algorithm.

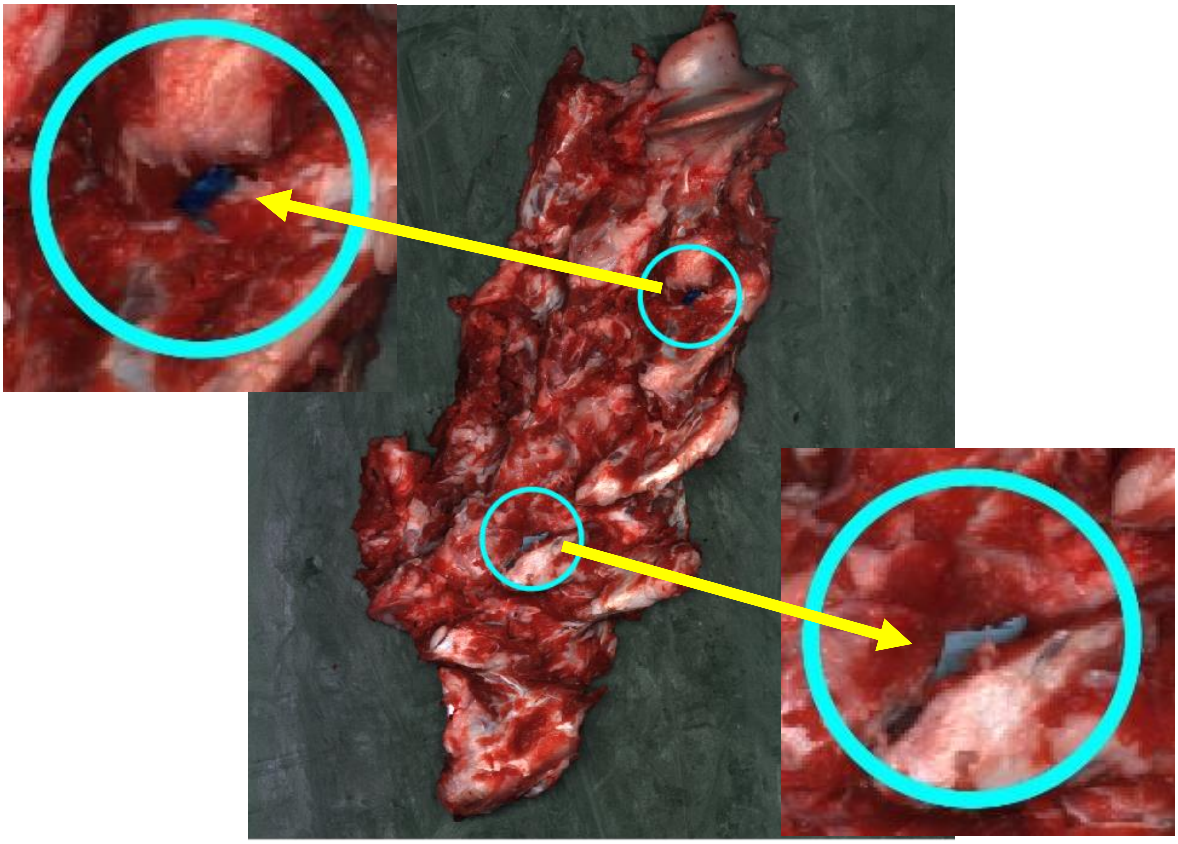

Figure 14. Example of two small pieces of plastic with different nuances of blue.

6.0 Discussion

The first two project phases were focused on preparing equipment, software, and procedures for data collection sessions. A 5-level trim score scale was defined as well as used and was found to give a good representation of the available bone samples sourced for the test from commercial processing facilities. It was found to work well in a development process as a tool for discussing trim quality in general steps.

Special trimming sessions provided bone samples in all 5 trim levels as well as weight data for the recovered meat from selected samples.

In Milestone 4, the datasets from the data collection sessions were analysed. The modelling effort focused on bone segment identification and estimation of recoverable product.

6.1 Bone Segment Identification

Bone segment identification models were developed by use of state-of-the-art machine learning techniques. The resulting models were able to correctly identify all bone segments with very high confidence. The few incorrectly labelled samples typically fell into 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 bones in a given pile to achieve valid yield performance KPI's on a continuously 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 it is expected to be a feasible approach as well.

6.2 Trim Quality Prediction

For vision, the amount of meat was estimated based on the pixel RGB+NIR values. Whitish pixels were classified as bone while deep red pixels were identified as meat. In between (pale reds and other colours), the classification became more difficult. A challenge here is that visual classification is often context-based. For instance, a pale red pixel is likely to be meat if found in a cluster of similar pixels and if located where meat is typically found.

For the vision-based method, only the surface is visible and does not offer much information about the thickness of the material. This makes vision better suited for certain bone segments. The neck bone, for instance, shows almost no white bone, and the soft-to-bone ratio therefore tends to be overestimated.

The number of red and white pixels for each image was used to estimate the amount of meat and bone. In turn, the trim score (or trim quality) can be predicted. 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, a significant overlap between the trim levels was also evident, especially for the central three trim levels.

The large level overlap is likely due to the uncertainty in the reference trim level data in combination with the difficulties in measuring meat-to-product accurately using 2D vision data. It is likely that the accuracy of the models can be improved by increasing the number of images in the training set.

For DEXA, bone and soft tissue thicknesses were estimated using a combination of specialized DEXA methods and machine learning techniques. It was found that the presence of bone over soft tissue invalidated soft tissue prediction, and soft tissue was therefore only predicted accurately outside bone structures. Consequently, the accuracy of the resulting meat-to-product ratio depended on the bone segment with the best results for bone segments that naturally exhibited meat on the bone edges. Loin bone, neck back bone, connected ribs and neck bones were all suitable candidates.

For the selected bone segments (loin and neck back bone), it was found that higher meat-to-product ratio indicated poorer trim quality, but with significant overlap between the trim levels. Part of the uncertainty can be ascribed to the reference trim score error, but it is unclear how much this affects the performance. The datasets used did not span the entire 5-level trim scale. This should be included in a next project stage with access to in-line data capturing with unlimited image data and variation. In general, significant improvements can be achieved by increasing the number of images in the training set, which would both average out some of the reference uncertainty and more clearly indicate outliers.

The developed trim quality prediction models are considered valid at the current stage for the purpose of monitoring the bone trim quality over a period. The models can certainly be improved with access to more training material and may also offer some advantages over vision-based methods for certain bone segments.

The combination of vision and DEXA data was approached through averaging the meat-to-product estimates from the two technologies and using the value for predicting the trim quality. It was found that the models became noticeably more accurate with a small level overlap for the two bone segments that were examined.

The improvement seemed to be beyond what can be expected from a simple mean reduction of the error. This is likely due to the two technologies relying on different physical principles and that they access different information. The DEXA method can detect the soft tissue and bone thicknesses (which vision cannot) but is incapable of measuring meat on top of bone (which vision can do). The two technologies therefore use information from different parts of the image, which is implicitly combined through averaging the meat-to-product ratios. For the combined model as well, it is likely that a larger training set would improve the general model performance in the same way as described above.

The combination of the two technologies is promising in that the combined model performs better than the individual models, but also because with both technologies more advanced model selection is possible. After identifying a bone segment, the technology that is best suited can be used for prediction. On the other hand, having both technologies will significantly increase the equipment cost, the complexity, and the operating costs; especially since the x-ray system requires special shielding and more involved safety testing, cleaning, and documentation.

Another factor to consider is that bones are unlikely to always be isolated on the bone belt. Rather, bones of mixed types on top of each other will pass the equipment at the same time. In these situations, x-ray information can assist bone segment identification but is unlikely to improve meat-to-product estimation much. This is because the DEXA models rely on the meat visible on the bone sides. In a pile of bones, this tissue is more likely to be obscured by other bones, reducing the value of the DEXA equipment.

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), especially if the bone result cannot be traced to the operator. 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 optimization tool, and that the accuracy can be improved with more training data.

7.0 Conclusions / Recommendations

During Milestones 1-4, it was demonstrated that it is possible to use a functional/prototype model with an integrated DEXA and RGB+NIR platform to retrieve and process simultaneous image and x-ray data from the two sensor principles. It provides parameters that correlate to potentially recoverable meat on bone, both as assessed by a visual appraisal and by actual weights.

During stage 2, experience towards a final industrial design was gained, and the hardware platform was, at the end of stage 2, prepared for at-line testing near production with larger product amounts and special cleaning procedures.

It was shown that the combination of DEXA and RGB+NIR sensor input provides better results than either of the two alone. However, it is also clear that for cattle bone applications there are limitations as to which bone segments can be robustly analyzed. For DEXA, thick bones tend to obscure meat and reduce the robustness of the analysis. For vision, only surface meat/bone is available for the analysis. Therefore, product type and orientation are an important factor for both technologies.

Monitoring the bone belt continuously allows for a 1:1 evaluation of all identifiable bone segments and would therefore offer a significant additional value to the cutting floor manager's sample control of the boning room work. 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 products for further processing for 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, including current level of performance in the boning room, the price of beef, production volume, the carcasses processed, and certainly how well the users are able to utilize the data for a continuous improvement of the operation, by training instructions etc. From pork deboning operations, it has been observed (through many Optimization/Yield boost projects) that increased focus, instruction and training can potentially result in a yearly benefit in the level of 1-3 million $ at the processors. With the current high beef prices, the potential could therefore be significant.

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 an additional 500 g of meat product on average from each carcass. This level of yield improvement is realistic considering that for most bone segments, each step up in boning quality on the employed 5-level scale corresponded to an additionally 50-500 g harvested meat (depending on bone segment). With this in mind, it seems feasible to achieve the above target without a significant impact on processing time, positively impacting the business case for the investment. Such an improvement is also 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 comparison, the few other meat industry solutions now available in the market, e.g., for meat/fat estimations, do not have the necessary aperture, and their price tags are significantly over that of a vision solution, perhaps in more than double or triple order. That is even comparing with a two side “waterfall” vision set up, which would allow looking at more of the bone surface and improving the estimate precision of recoverable meat potential to be harvested.

The combined DEXA and RGB+NIR platform at hand for stage 2 had an aperture limited to 40 cm wide and 12 cm height, not allowing to test all bone segments. To cope with all bone sizes, a much larger equipment aperture and footprint will be required, or bones would need to be desized. Larger size aperture requires a larger x-ray detector at a higher price tag, and footprint. From a technical, component and development view, this is a fully feasible transition to put in the market. However, development is required as no such solution is immediately available.

It must also be noted that the required associated costs for integrating DEXA in a line setup are much higher than for a vision system mounted over a line only.

With respect to operating and servicing cost over a lifetime, it is also worth to consider that x-ray systems need higher user safety standards, robust shielding solutions and are more time consuming to clean. Therefore, the running costs for a solution including DEXA will be in higher than for a vision system. As an example, DMRI is servicing the BCC-2 vision platforms, as some systems are still in use after 25 years, with very marginal service, parts change or upgrades required.

Given the above implications of using a DEXA and RGB+NIR combined platform, the DEXA technology requirement will come at both a higher CAPEX and OPEX. It is relevant to balance whether the proven minor increase in precision of the recoverable meat to be harvested can justify the increased complexity and cost, over a simpler Vision solution.

In the AMPC and industry context, it is recommended to start out at an Australian processors bone belt with focus on validating how much of the potential can be harvested by vision set up alone. If the potential and value creation is very significant, the next likely step up could be to explore either a 2 or 3 side free fall/waterfall vision solution compared with a combined DEXA and RGB+NIR solution.

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