

Bone belt monitoring

In line validation and demonstration

Vision RBG stage 3-4

Project code
2024-1072

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Contents

Contents	2
1.0 Abstract	4
2.0 Executive summary	4
3.0 Introduction	5
4.0 Project objectives	6
5.0 Methodology	6
5.1 General overview	6
5.2 Installation	6
5.3 Data collection	8
5.2 Segmentation for bone type and quality	9
5.4 Design of KPI dashboard	13
6.0 Results	15
6.2 Trim quality	16
7.0 Discussion	16
8.0 Conclusions	18
9.0 Recommendations	18
10.0 Project outputs	19
11.0 Bibliography	19
12.0 Appendices	20
12.1 Examples of trim levels	20
12.2 Bone types used	24
12.3 Confusion matrices for trim level models	25

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1.0 Abstract

The beef processing industry faces significant yield losses when valuable meat is left on bones during the deboning process. With the rising beef prices in the market and falling supply the importance of high yields in the boning room has become even more important in recent years. Because manual quality audits are time-consuming and capture only small samples, these inefficiencies often go unnoticed. This project was undertaken to validate and demonstrate a continuous, vision-based in-line monitoring solution that acts as an automated yield auditor for the bone belt.

To achieve this, the development team designed, built, and installed a washdown-ready, food-grade RGB vision system above the main bone belt of a major Danish beef processing facility. Using an area scan camera and customized illumination, the system continuously captures overlapping image segments of the moving product stream. These images are stitched and segmented using advanced AI-based object detection algorithms.

The AI model was trained to recognize and categorize bones into 21 distinct types and assign a 4-point trim quality score (ranging from "great" to "bad" trim with significant meat left) for initially five key high-value bone types. Finally, a real-time KPI dashboard was designed in collaboration with the plant users, and specialists in yield optimization to visualize yield trends, daily grades, and major deviations.

The key results demonstrate that the vision system successfully runs in-line at full production speeds, segmenting individual bones and feeding the KPI dashboard in real time for the target bone segments. For the industry, this technology provides plant managers with continuous, 1:1 visibility of deboning room performance. By identifying training opportunities and managing day-to-day process deviations, processors may realistically harvest at least an extra 500 grams of meat per carcass, translating to a rapid investment payback period of only 6-36 months.

2.0 Executive summary

Optimizing carcass yield in a beef deboning room is a primary driver of processor profitability. However, keeping track of deboning quality is notoriously difficult. Valuable meat left on bones is quickly lost to the bone belt, an "out of sight, out of mind" issue. Traditional manual batch checks are often sporadic and less insufficient for managing continuous process control with lasting corrective effects.

This research was conducted to transition a previously validated laboratory-scale RGB-vision AI concept into a fully operational, in-line industrial prototype. By providing real-time, continuous monitoring of bone trim quality, the system acts as a direct feedback loop for supervisors, enabling them to identify specific deboning mistakes, retrain operators, manage day-to-day corrective actions, and prevent valuable product from being sold as low-value by-product.

The project successfully achieved its core objectives:

- Demonstrated continuous, stable in-line image capture and data collection of bones directly from an active industrial bone belt
- Developed AI-driven image segmentation and stitching models to isolate individual bone products from the conveyor background
- Trained AI classification models to accurately identify bone types and evaluate remaining meat levels using a standardized 4-point trim scale

- Designed and successfully demonstrated a practical, real-time KPI dashboard for use by the plant at different levels to visualize daily yields, track performance trends, use for instructions and corrective actions

The vision system enclosed in a washdown-safe steel cabinet was built and installed above a bone belt at a Danish beef processing facility, capturing bones from both the forequarter and hindquarter lines. The system captured overlapping images of the moving belt, which were stitched together and segmented using deep learning algorithms. Bone images were annotated into 21 specific bone types. For five bone types with a high harvest potential, an expert butcher established a training baseline by annotating images into four distinct trim quality levels (Grade 1 for "great trim" to Grade 4 for "bad trim"). A web-based KPI dashboard was developed in consultation with user yield experts to display live yield statistics.

The prototype successfully processed the continuous product stream in real-time. The AI models effectively classified the five target bone types and estimated their trim quality, with accuracy levels steadily improving over successive training iterations. The imbalance in the grade types (few class 3 and 4 with much meat left over) called for extensive data collection period with a potential to improve further over time. Plant users and yield specialist reviewed the live dashboard outputs and validated the system's tracking and reporting capabilities as highly relevant.

This technology transitions yield monitoring from manual low-level sampling to proactive, 100% continuous auditing. By utilizing the dashboard to identify and rectify poor trimming, processors can realistically harvest more high value meat. The potential will vary between processors depending current volume, raw material, procedures, yield levels achieved, boning salary methods and management systems applied. It is estimated for most processors minimum average of 100-500 grams of additional meat per carcass should be feasible. At current high beef prices, this adjustment in yields over time gives significant financial gains, allowing processors to achieve full payback on a \$150,000 to \$200,000 AUD technology investment within just 6 months to 36 months. It also perfectly aligns with global sustainability goals by maximizing human food yield from every animal.

To drive industry adoption, future work may focus on integrating the bone belt vision data further with the processor's Manufacturing Execution Systems (MES) to correlate trim quality with specific carcass batches. Additionally, to explore feasibility of using the real-time data to trigger automated sorting gates, redirecting poorly trimmed bones to a re-trimming station automatically.

3.0 Introduction

The yield performance of a deboning room can indirectly be monitored by the amount of remaining meat still present on the bones at the bone belt. This method of removing by-product from the room is also a common way to forget mistakes at the deboning line, out of sight, out of mind, but with drawbacks in performance yield.

DMRI-DTI has been studying the task of measuring meat-to-bone ratio using a vision-system with segmentation- and scoring algorithms within the previous AMPC-project: *"Bone Belt Monitoring – Vision RGB+NIR Stage 2, 2021-1175"* (Stentebjerg & Madsen, 2022).

The project focused on algorithm development based upon offline data collection performed in lab-test with a variety of bones sourced from local beef processors in Denmark. The results showed feasible methods for estimating meat-to-bone ratio plus an AI classification model for predicting trim scores on relevant selected bone segments. Based

upon the results of this project, unfolds the current project, which include demonstration of an in-line solution for monitoring the bone belt.

Boning operations are performed globally with varying skills and results. Any inline monitoring tool of processing quality that can provide insight and help corrective actions should have value and interest from processors to produce with higher yields and profits.

4.0 Project objectives

The objectives of the project are:

- Demonstrate the capability of continuous vision monitoring of the bone belt at a processing facility with the ability to acquire a dataset of selected bone segments
- Develop recognition algorithms based on AI-modelling to identify relevant bone segments
- Develop assessment algorithms to estimate a score for the remaining level of meat on bone segments
- Design and test reporting tools for KPI-data visualization in the form of a dashboard design, that is practical and meaningful at the operation level as aid to optimize yield

5.0 Methodology

The vision equipment was installed and started to collect image from primo 2025 and has run continuously since collecting data for the AI modelling and the results dashboard development, test, use and demonstration purpose.

5.1 General overview

This section details how data collection over the line at the processor was collected for training and dashboard reporting purposes.

An overview of what models are live on the installed unit will be given along with how key metrics collected from the models are shown to the user in the dashboard format.

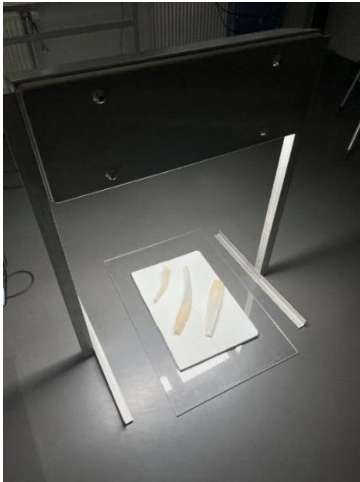
A summary of the first evaluation with end users at the processor plant will be given along with details for further planned refinement of dashboard and models.

5.2 Installation

Danish Beef Processor facilities were studied and visited by the team to determine the best setup and location for the installation of an in-line monitoring system above the bone belt. It was essential to secure a position with enough

free space to contain a general footprint of the measurement system, as well as the possibility to majority of bone segments forequarter and hindquarter.

The team built an industrial vision system, that consists of an RGB area scan camera illuminated by a LED-panel, all enclosed in a steel-cabinet, which was designed to stand the environment of a food processing facility. The solution is equipped with an internal mini-PC for controlling the image collection and the real-time image analysis. Below is the vision system at pre-install testing.

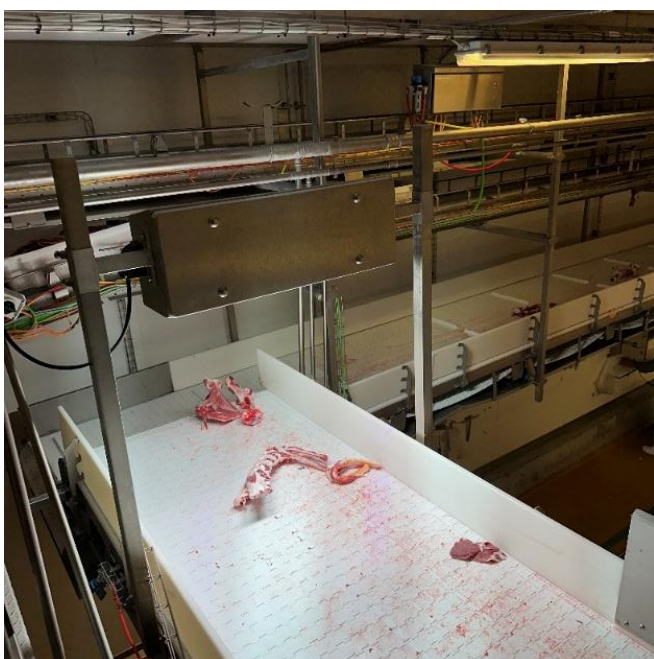


The vision solution during test and configuration at DMRI.

The vision solution has been configured to measure the full width of the bone belt by determining the desired height above the conveyor as well as configuring light and camera settings to accommodate the speed of the conveyor belt.

Furthermore, a mounting setup was produced in collaboration with the beef processor to safely mount the vision system in the correct height and position above the bone belt.

Below is the final installation of the vision system above the processors bone belt. The equipment is placed after two conveyors feeding with bone segments from both forequarter and hindquarter.



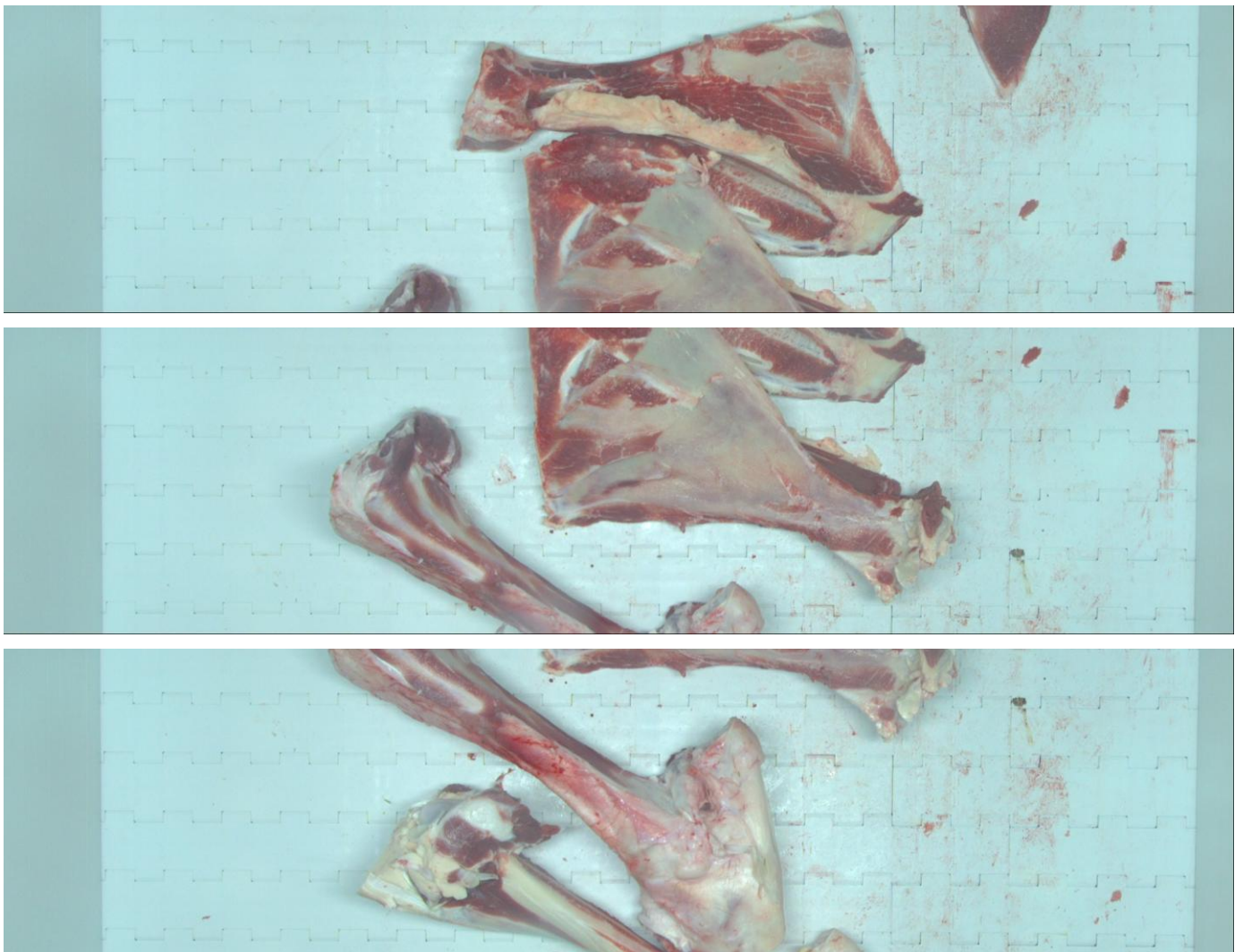
Final test setup after installation of the vision solution above the bone belt

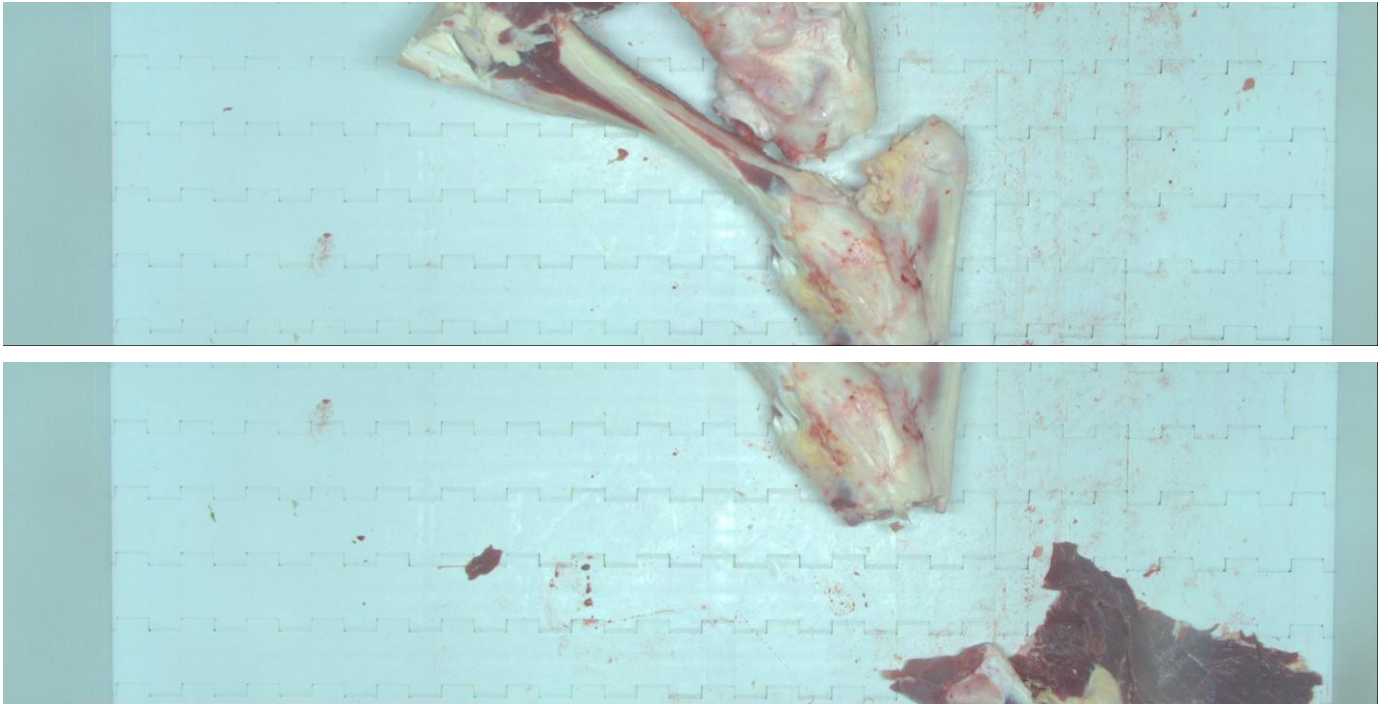
5.3 Data collection

The camera system is based on a RGB area scan camera. The decision for a more standardized vision setup (compared to multispectral) is based on the consideration of cost efficiency as well as the capability to segment out meat, fat and bone from the conveyor background based on RGB-pixels alone.

The challenge of the data collection process is to secure a robust way of joining image segments together with bone segments in variable dimensions, presentations and especially height on the belt. The solution was built by continuous overlapping image acquisition of the camera, obtaining parts of bones moving within the camera field-of-view. As the bone segments are also of different shapes and sizes, the raw images must be connected according to the bone segment position on the conveyor. Orientation of bones on the belt is not uniform but with enough segments a broad representation of bone orientation still allows correct recognition. A threshold can be set to accept bone segments only with a high recognition rate.

Below is shown an example of 4 individual bones, 2 Blade bones (Scapula) and 2 Hind Shin bones (Tibia) captured in 5 different raw image segments. Notice the rather large overlap between the captured image segments, which is applied to secure sufficient pixel data for the segmentation algorithm to join multiple sets of images of the same individual bone segment.





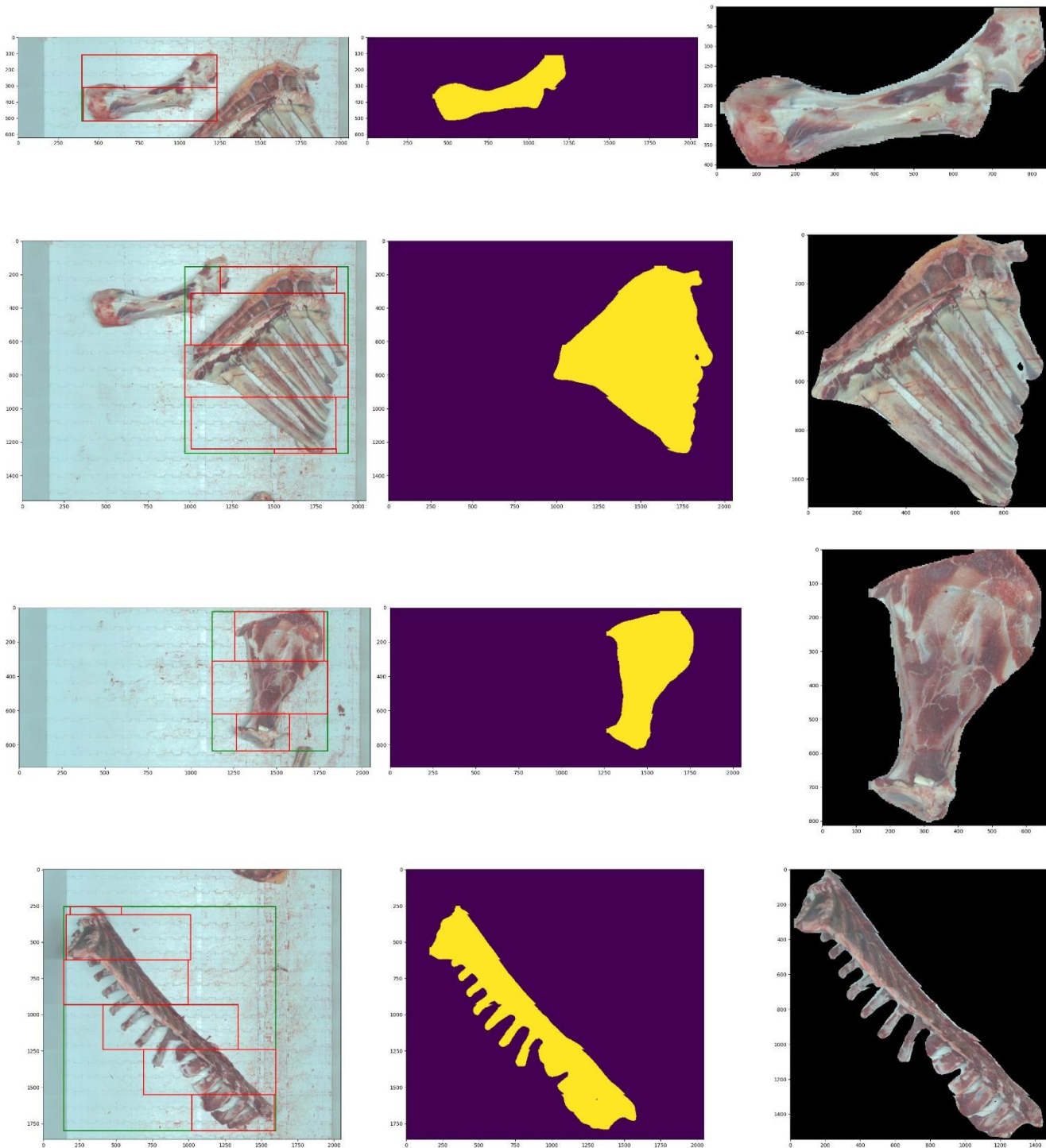
5.2 Segmentation for bone type and quality

Raw image data was used to first segment out images for individual bone type classification and then following a trim score classification was done on individual bone types.

5.2.3 Bone type segmentation

With the raw images described in the previous section a series of AI models was trained to segment out individual bones on the conveyor belt. An initial model detects foreground object and isolate the bone products from the conveyor belt background. Algorithmically, bounding boxes that overlap with neighbours are joined together to form full bone pieces that are then cropped and have the background masked out as seen below: the red boxes are individual detections joined based on overlap at top/bottom of the bounding box. The green boxes are the crop for the full bone piece.

In situations where more bone segments are overlapping to an extent that does not allow a safe recognition in the analysis, these segments are disregarded in the further KPI analysis. This seems a sound approach as the overlapping products are considered random occurring. Longer term a mechanical spreading of the bones might be considered if not cost excessive.



After the algorithms to separate and join bone objects together was in place, annotation of the bones took place into 21 bone categories and some unspecified item. Bone segment images was saved locally to the device with accompanying annotation files. Bonetype and quality score was also saved into a database for use with the dashboard. To focus the time spent on annotation in the next stage for better results, 5

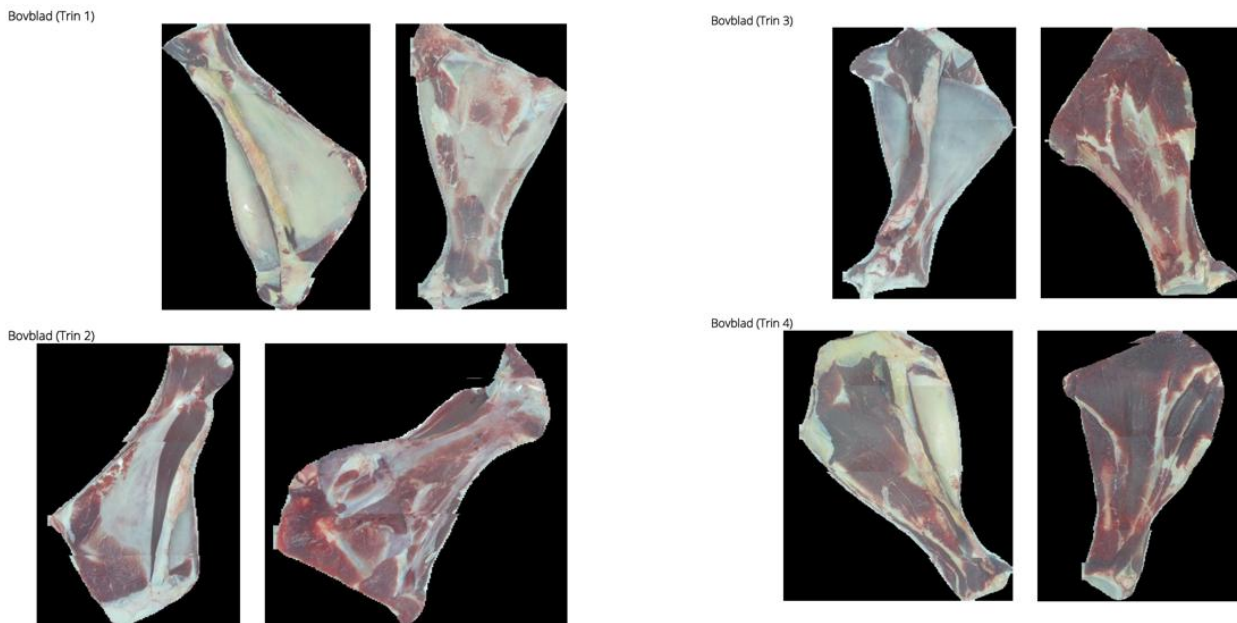
bone types considered with a high harvest potential for leftover meat, were selected for the initial quality models: Back bone (pistola), neck bone, blade bone, blade bone cartilage, Back bone (wing).

5.2.3 Trim quality modelling

Following object detection and stitching, in the third stage, a trim-score model was applied to each bone type. Trim levels were separated into four categories:

Quality	Description
1	Great trim
2	Acceptable trim
3	Lacking
4	Bad trim, too much meat left

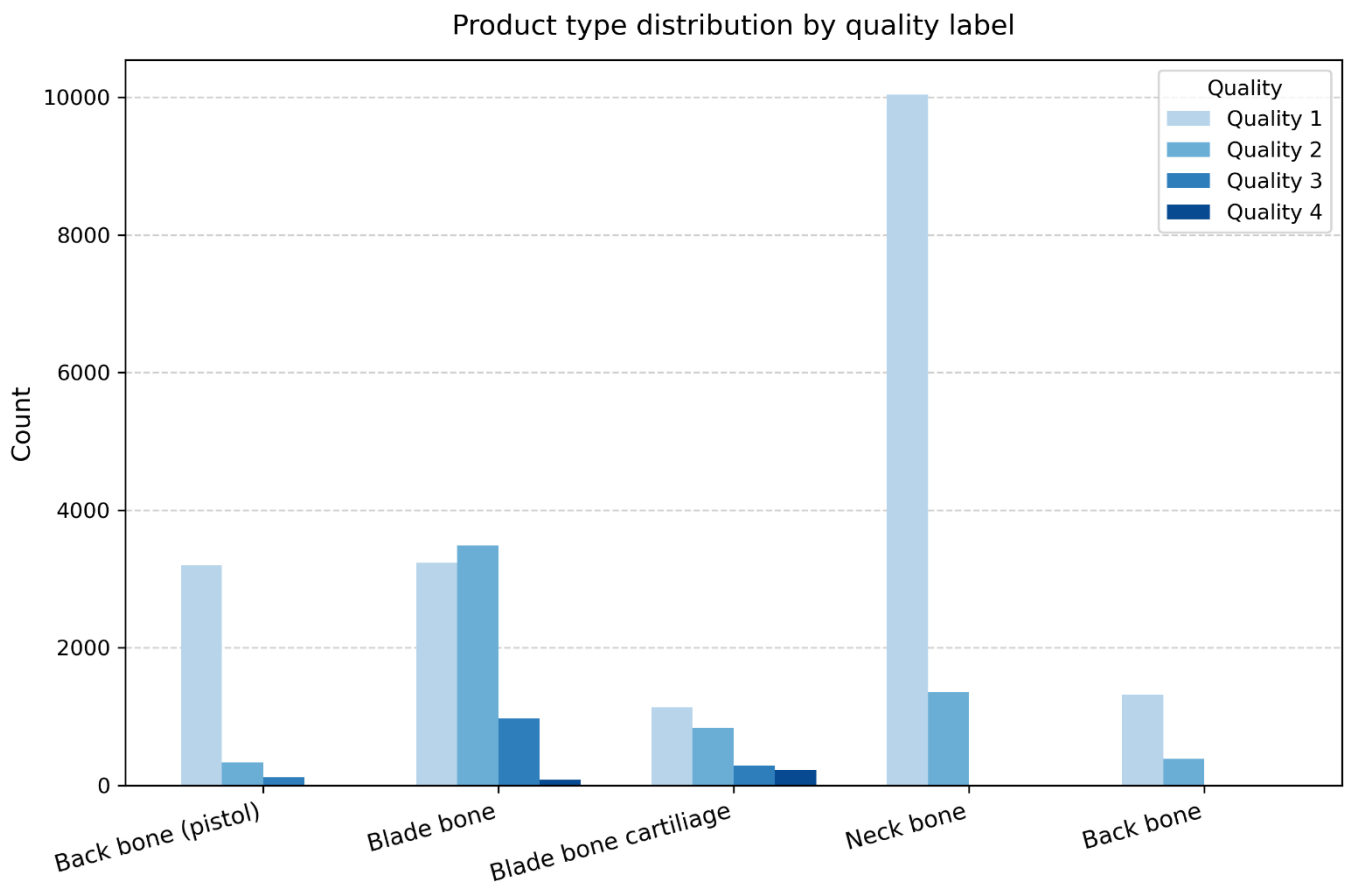
For the five select bone types, data was annotated into 4 classes by a trained butcher with experience in deboning. An example of the four different trim levels can be seen here:



Trimclass levels 1 to 4 for Blade bone (scapula “Bovblad”) above

After initial annotation and training and modelling it became evident that there is no balanced output of the 4 scores coming through daily. From a processor perspective it is positive that there are mainly trim 1 and trim 2 scores represented whereas the level 3 and 4 are less frequent. From a model training perspective, it requires more time to search through acquired images and review the models scores and reannotate if necessary.

The below graphs show the imbalance of product type and quality levels witnessed in data collected from 15 workdays in Q2 2026.



5.3.1 Annotation software for quick annotation of bone type and trim score

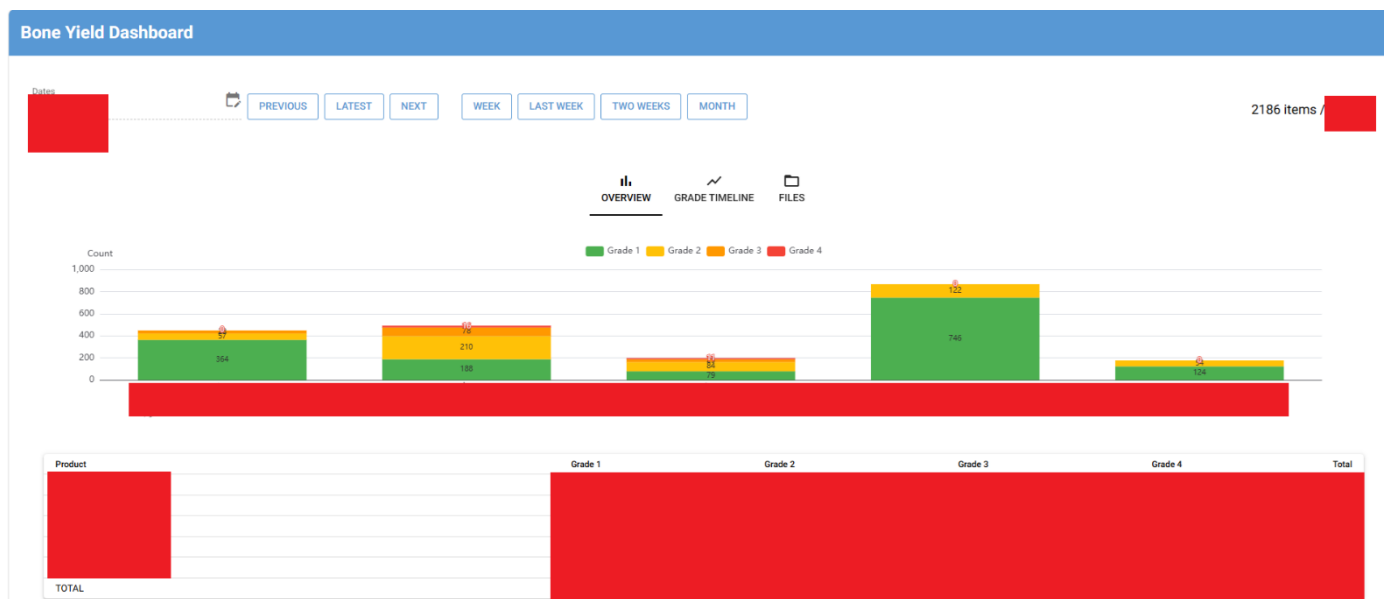
To streamline the annotation process, a simplified annotation tool was developed that can be used by our own boning experts and made available to users at the processing plants. This will speed up effective additional annotation of more bone products in various classes and be handy for intercalibrations.



Annotation GUI used for scoring the Trim level (1-4)

5.4 Design of KPI dashboard

To inform the end user with live reporting of current trim levels for select bone types, a dashboard design was developed and implemented to give a KPI overview of trim levels. The dashboard viewer is setup to check real time for images saved and can give live updates on all images captured over the production line. The design goal is to have a dashboard **Overview** that quickly lets the operator inspect what the general trim level is for all bone types and let the user inspect the individual bone segments if relevant.



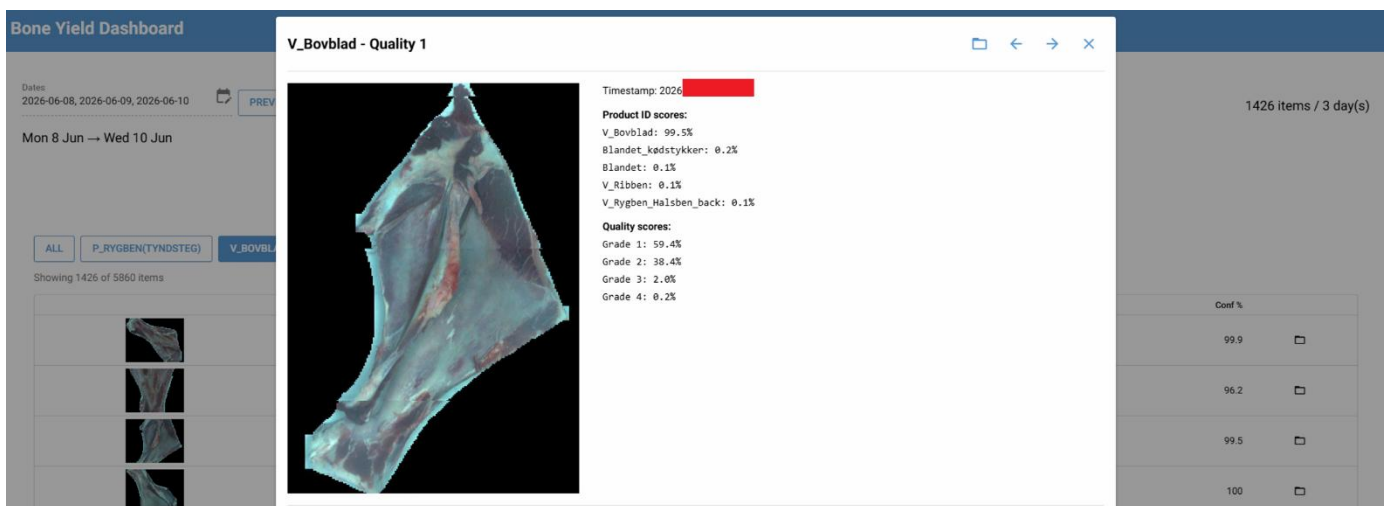
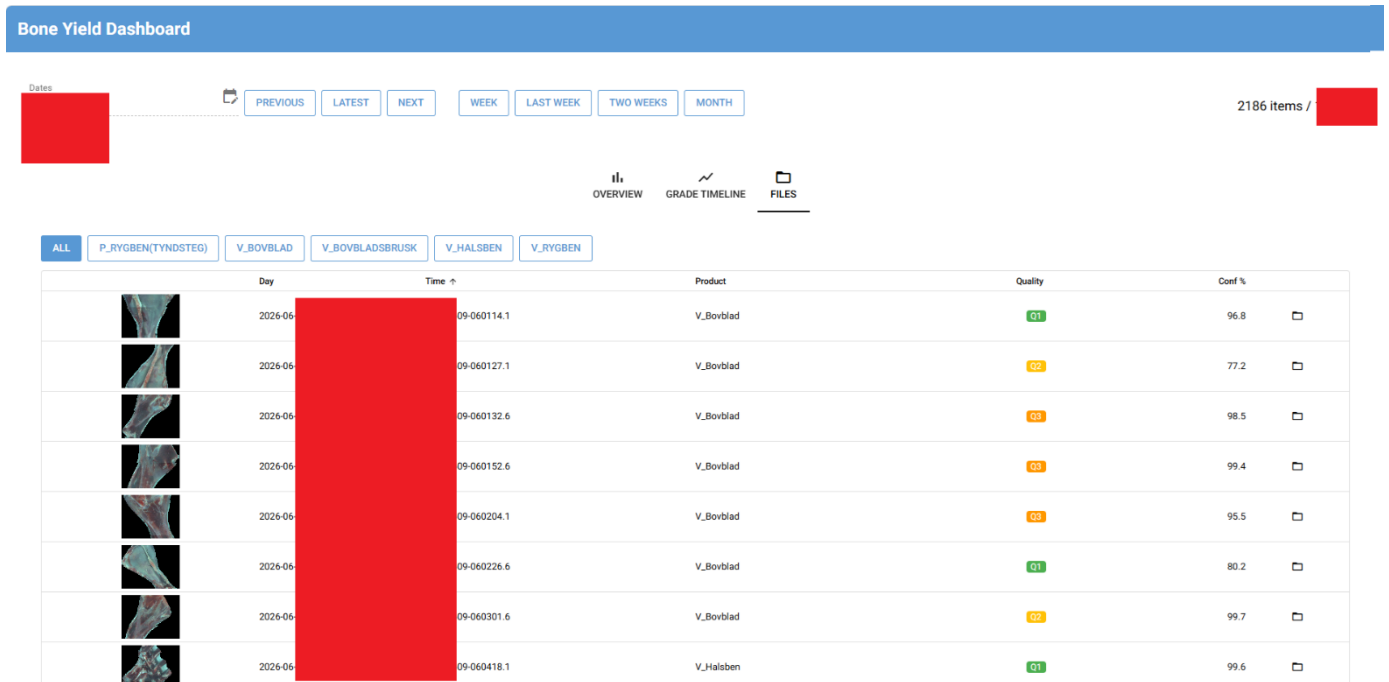
The dashboard shows a bar graph with the number of products recognized in the 5 types used for the initial testing as well as the trim level within the types.

In the top the user can choose the time period to review, starting at the latest day of data, but the range can be modified for a selected period. Larger versions of the dashboard are shown in the appendix.

The **'Grade Timeline'** tab shows how trimming levels have varied over the production period for each selected bone type.



The **'Files'** tab can be used to inspect the individual images and their related classification. This is most useful for reviewing findings and class levels with the users during finetuning of models and the dashboard. The option to select images for examples of do's and don'ts have been useful for the processor internal communication.



During initial dialogues about the dashboard the users have found the initial layout and selection options viable and relevant.

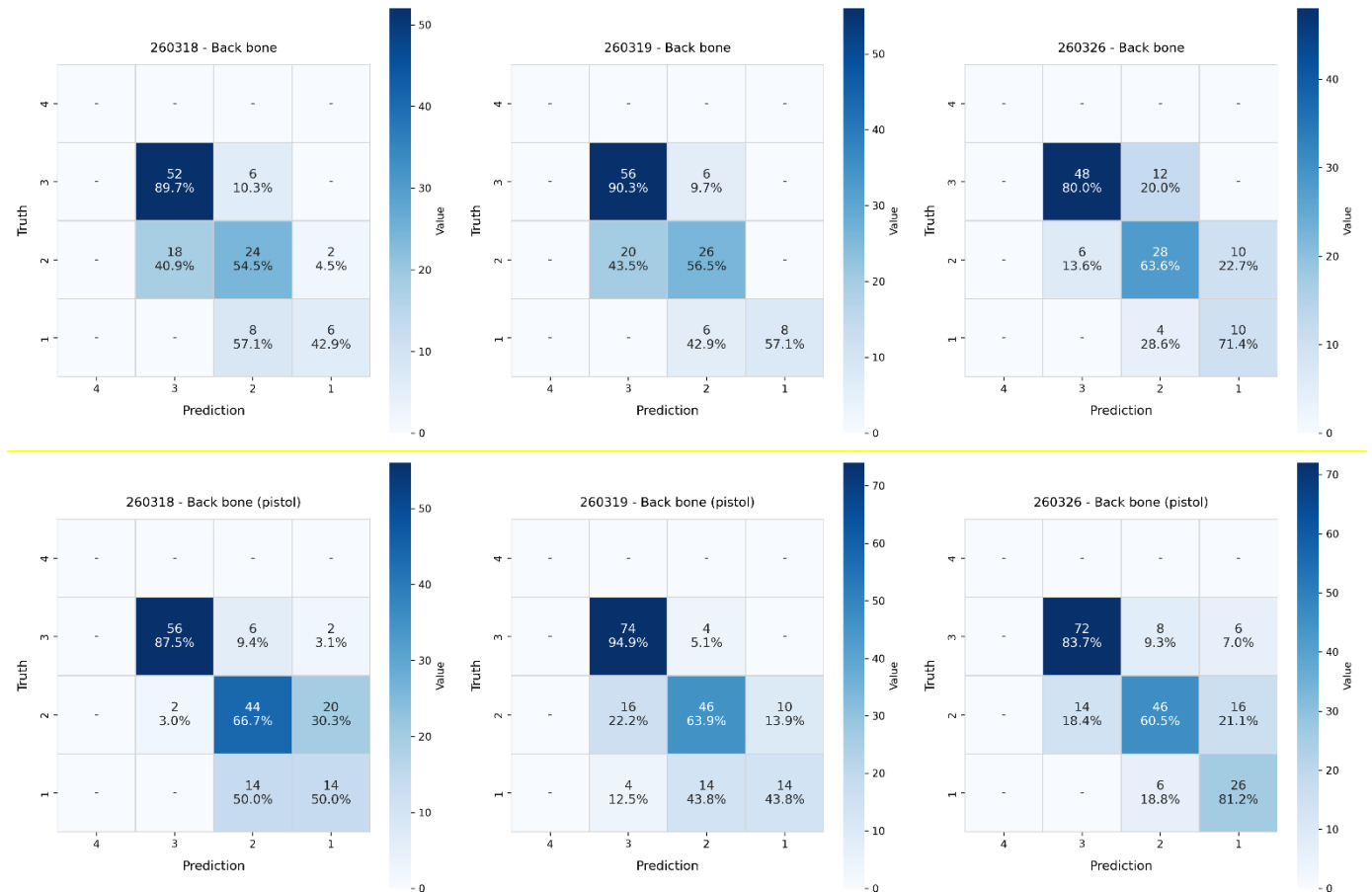
There is ongoing dialog with the users to get more feedback on the layout of the dashboard for later improvements.

6.0 Results

In the first milestone of the project the measurement unit was designed and installed on site at a Danish Beef Processor facility. Following this AI models for bone type and trim quality came online for 5 bone types, using the acquired in-line data. Trim quality is viewable immediately in a dashboard format live on the unit.

6.2 Trim quality

With annotation of additional data over time, the accuracy of the trim model is getting better, although low availability in some classes can still lead to a higher inaccuracy. Below is an overview of 3 stages of model training for the 2 bone types: back bone and back bone(pistol). The examples show the accuracy of the models tested on a smaller test segment of the available training data.



What can be observed in the plots above is an overview of how often the model prediction (x-axis) fits with the correct label from annotation (y-axis). Over time we observe a general increase in correct predictions for trim class 3 – 1 but no trim class 4 was found for this time period.

The training also reveals that the greatest overlap between trim levels is around 2nd level being misclassified as either 1 or 3. To overcome this, the first goal is to filter out only collected bone segments of the underrepresented classes for verification and adding those to improve the model further.

7.0 Discussion

It is possible for the current equipment to keep up with the production line and deliver timely information in a dashboard format.

Due to a busy season at the processing plant extended feedback and review of the dashboard has not been fully achieved yet and will come during the next 6 months where the project continues through other funding.

Further refinement of the user interface based on operator needs is expected in this period, as well as continual refinement of more bone and trim models following regular data annotations.

To contextualize the commercial viability of the current camera and dashboard solution demonstrated, it is worth referring to the economic considerations established in the preceding final report: Bone Belt Monitoring – Vision RGB+NIR Stage 2, AMPC 2021-1175 (2022). These estimates and evaluations remain highly relevant and are updated below to the results here:

- **Technology Investment:** The previous stage estimated the Recommended Retail Price (RRP) for a fully established boning line system to be between **\$150,000 and \$200,000 AUD** (adjusted to 2027 price levels, including commissioning, which is largely an adaptation of the model to prevailing biological bone type variations and presentations). Final pricing is subject to variations in installation scope, volume of targeted bone units, and plant integration.
- **Achievable Yield Targets:** Based on the 5-point boning quality score used in Stage 2, moving up just one step on the scale recovered an additional 50 to 500 grams of meat per bone segment (depending on the specific bone). Across bone segments a better scale point in yield class typically averaged 200g product.

By utilizing the dashboard to identify and rectify poor trimming, processors can realistically harvest more high value meat. The potential will vary between processors depending current volumes, raw material, procedures, present yield levels, boning salary methods and management systems applied. It is estimated for most processors minimum average of 100-500 grams of additional meat per carcass should be feasible using a data driven approach. It is a prerequisite that data are used actively with corrective actions on the boning floor and /or sending high potential bones for retrimming

- **ROI** At current high beef prices, this adjustment in yields over time gives significant financial gains, allowing processors to achieve full payback on a \$150,000 to \$200,000 AUD technology investment within just 6 months to 36 months. With management, training instructions it is considered feasible to harvest more meat without slowing down line processing or increasing risk of cartilage or bone splinters in products.
- **Rapid Payback and ROI:** With average of 100-500 grams of additional meat per carcass an average, most large processors can expect an estimated payback period of 6-36 months, depending on production volume, and the actively working with data, and with the boning operators. Incentive payment models might be considered
- **Industry Precedence:** Historically, implementing data-driven focus, instructions, and frequent checks and periodical training in larger pork deboning operations has driven annual yield boosts worth \$1 million to \$3 million AUD. Given sustained high beef prices, the financial upside for beef processors is expected also to be significant
- **Strategic and Environmental Alignment:** Beyond direct profitability, utilizing this KPI dashboard to minimize meat waste directly aligns very well with global sustainability mandates to "do more with less," optimizing carcass utilization before by-products are diverted often to non-human side streams

8.0 Conclusions

A in-line monitoring solution for the Bone belt has been developed and deployed working and collecting data for more than 18 months. AI models identifying individual bone segments have been developed and likewise AI model that can score the quality of deboning in 4 levels of 5 targets bone products have been developed and are working in the line.

A KPI dashboard solution has been developed and initially found highly relevant at the processor manager level. Further evaluations are ongoing throughout 2026 on other funding.

As presented here and in the previous work stage 2, the 1:1 continuous coverage of the bonebelt based on real data is considered a very valuable tool for the cutting floor manager, instead of only relying on few random samples or more costly operator checkpoints.

As the work using the measurement device and dashboard at the processor continues, the work regarding the objective of designing statistics, reporting and alerts regarding the real time KPI data presented in the dashboard is expected to continue and being further refined throughout 2026.

Once the data acquisition system is installed at a processing plant, using it for foreign object detection is also a possibility though it requires its own data gathering and annotation. But reporting could happen via the same dashboard as for trim scores, giving the cutting floor manager one unified view of relevant real time data from images.

9.0 Recommendations

It would be worth looking into how to correlate data from the Bone Belt monitoring with data in a processors other data system, both for verifying the coverage of products on the bone belt and to get more accurate metrics for the value that can be harvested. If bone images can be tied directly to product batches estimating payback time and reporting would be simpler.

A future improvement to the monitoring systems would be to use its data to redirect products with poorest trim scores back for retrimming automatically.

Once the data acquisition system is installed at a processing plant, using it for larger foreign object detections is also a possibility, though it requires its own data gathering and annotation. This use is highly relevant in bone products assigned for eg. soup or soup stock processing. The reporting could happen via the same dashboard as for trim scores, giving the cutting floor manager one unified view of relevant real time data from images. Likewise, an automatic reject station can be actuated to remove the foreign objects on the belt.

It is considered relevant to migrate the solution to an Australian beef processor to demonstrate, adapt and validate further in this processing environment. The hardware and software platforms are

considered viable and possible to optimise respective the models from remote and with local processor intercalibration of annotations and trim score levels.

10.0 Project outputs

This project has resulted in the installation of an in-line measurement solution at Danish Beef Processing plant for data acquisition and live bone belt monitoring.

The measurement unit features image acquisition hardware and software capable of monitoring the bone belt real-time. The software runs multiple layers of AI capable of classifying bone and trim level within bone type. The camera housing is made to withstand the harsh climate of a processing floor for continuous use.

The unit also hosts a dashboard giving an operator or the cutting floor manager access to KPI insights for the recognized bone types.

A large dataset of biological variation covering of total of approximately 236.000 bone segments and 13.000 annotated bones with trim scores. Software AI models has been developed for use and continual improvement of the Bone Belt monitoring system.

11.0 Bibliography

P. R. B. Stentebjerg and N. T. Madsen, DMRI, Bone Belt Monitoring – Vision RGB+NIR, Stage 2, Final Report, Published 30/05/2022

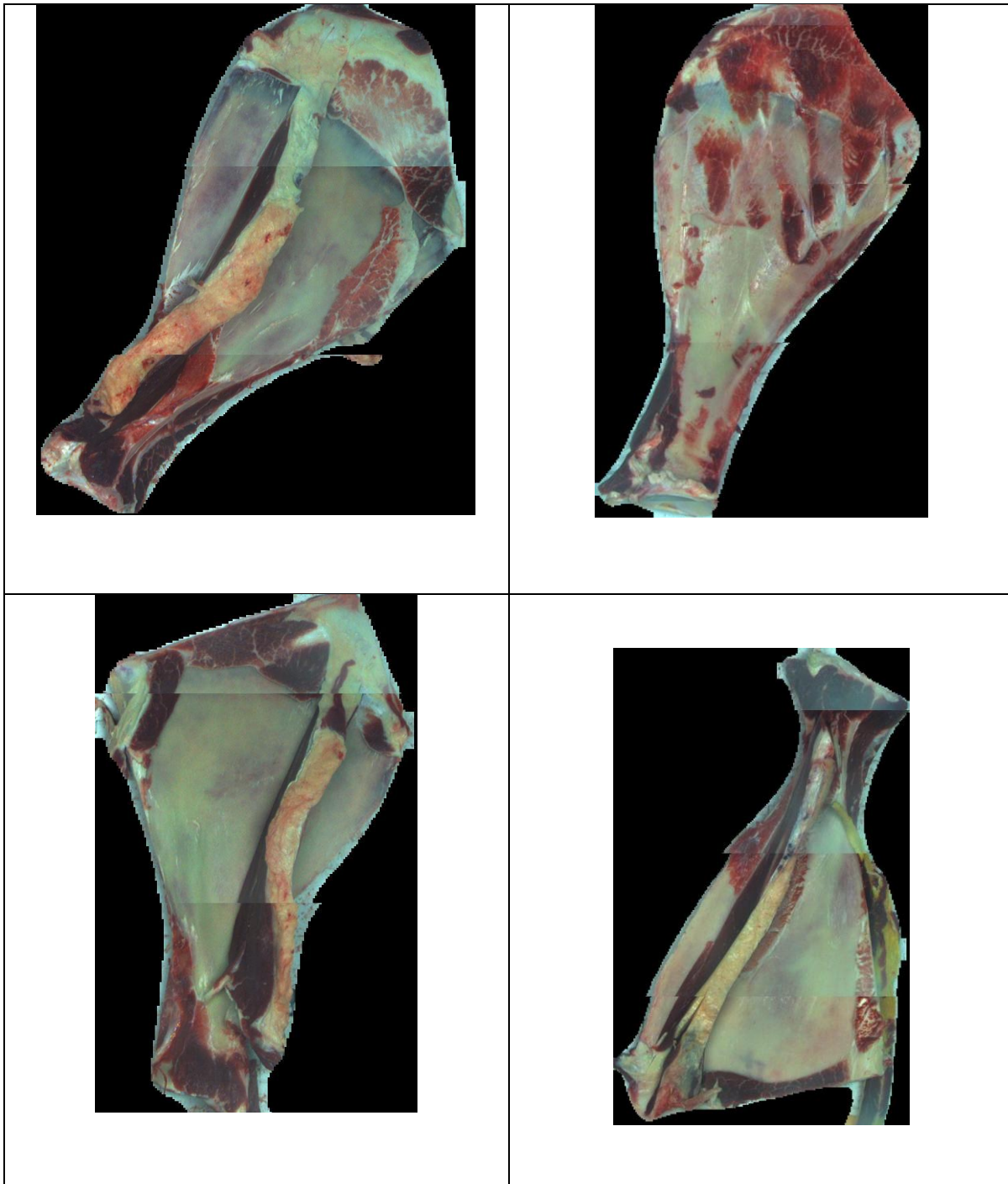
P. R. B. Stentebjerg and N. T. Madsen, DMRI, Bone Belt Monitoring – Vision RGB+NIR, Stage 3-4, Milestone Report, Published 31/03/2025

12.0 Appendices

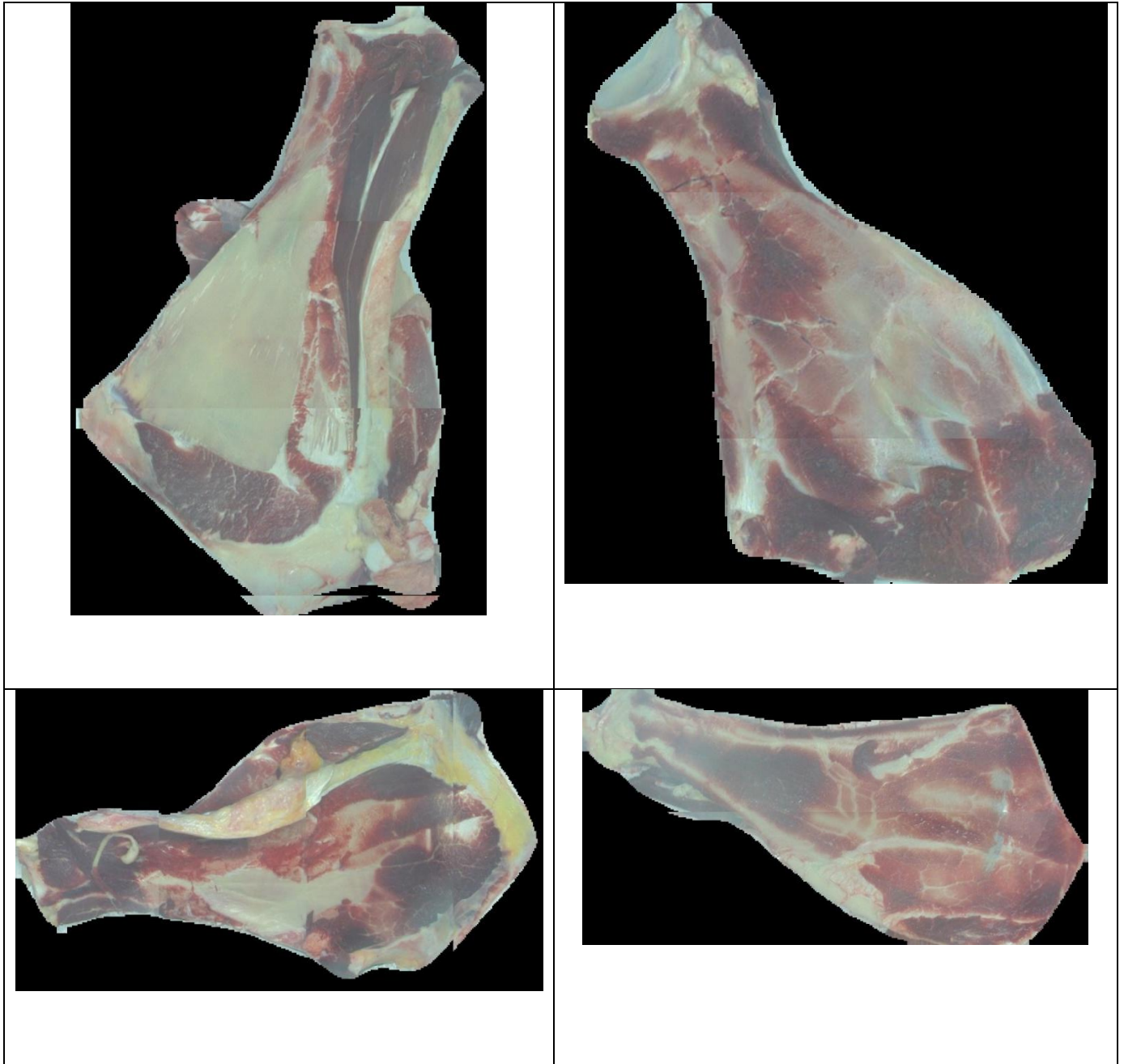
12.1 Examples of trim levels

Grade blade bone

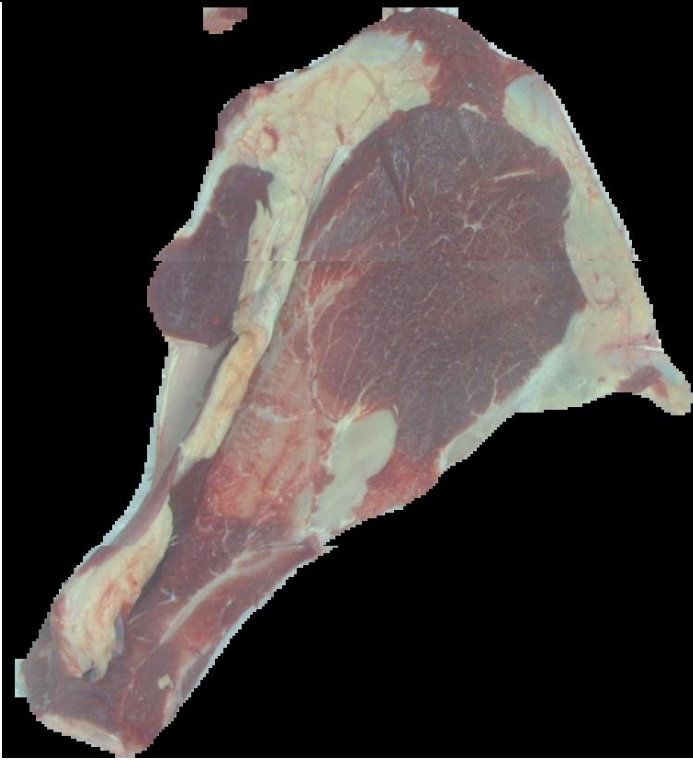
Grade 1



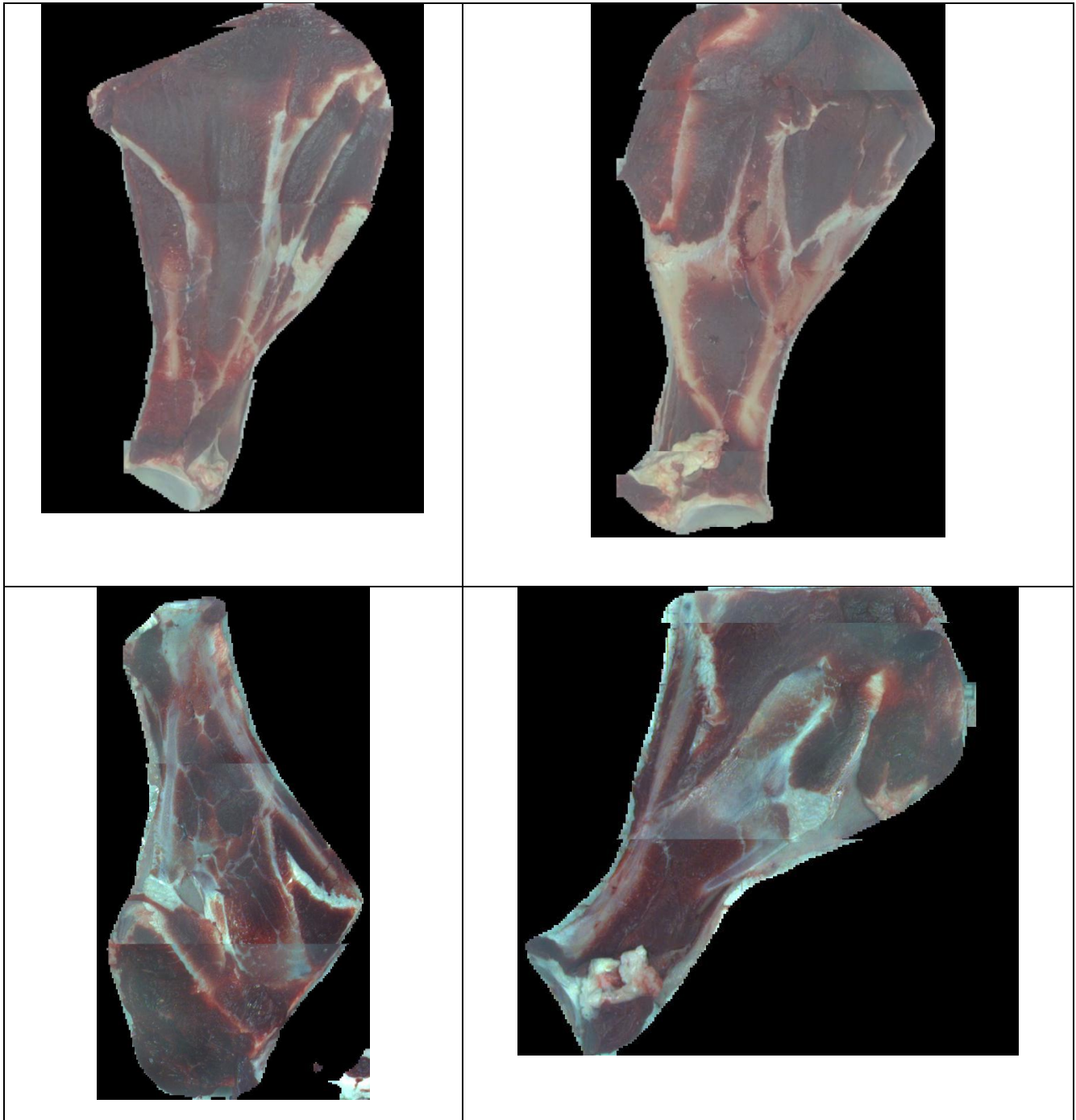
Grade 2



Grade 3



Grade 4

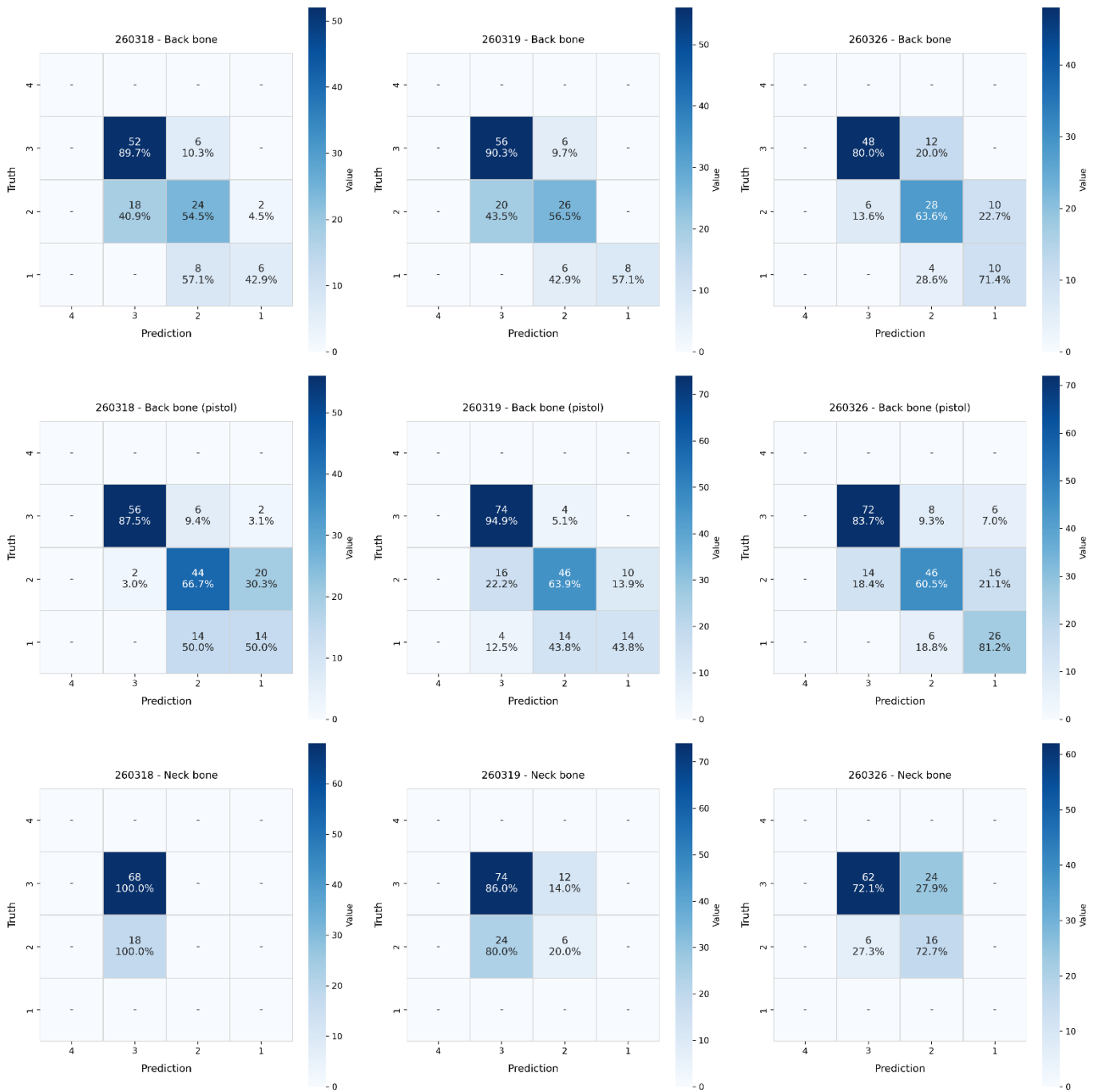


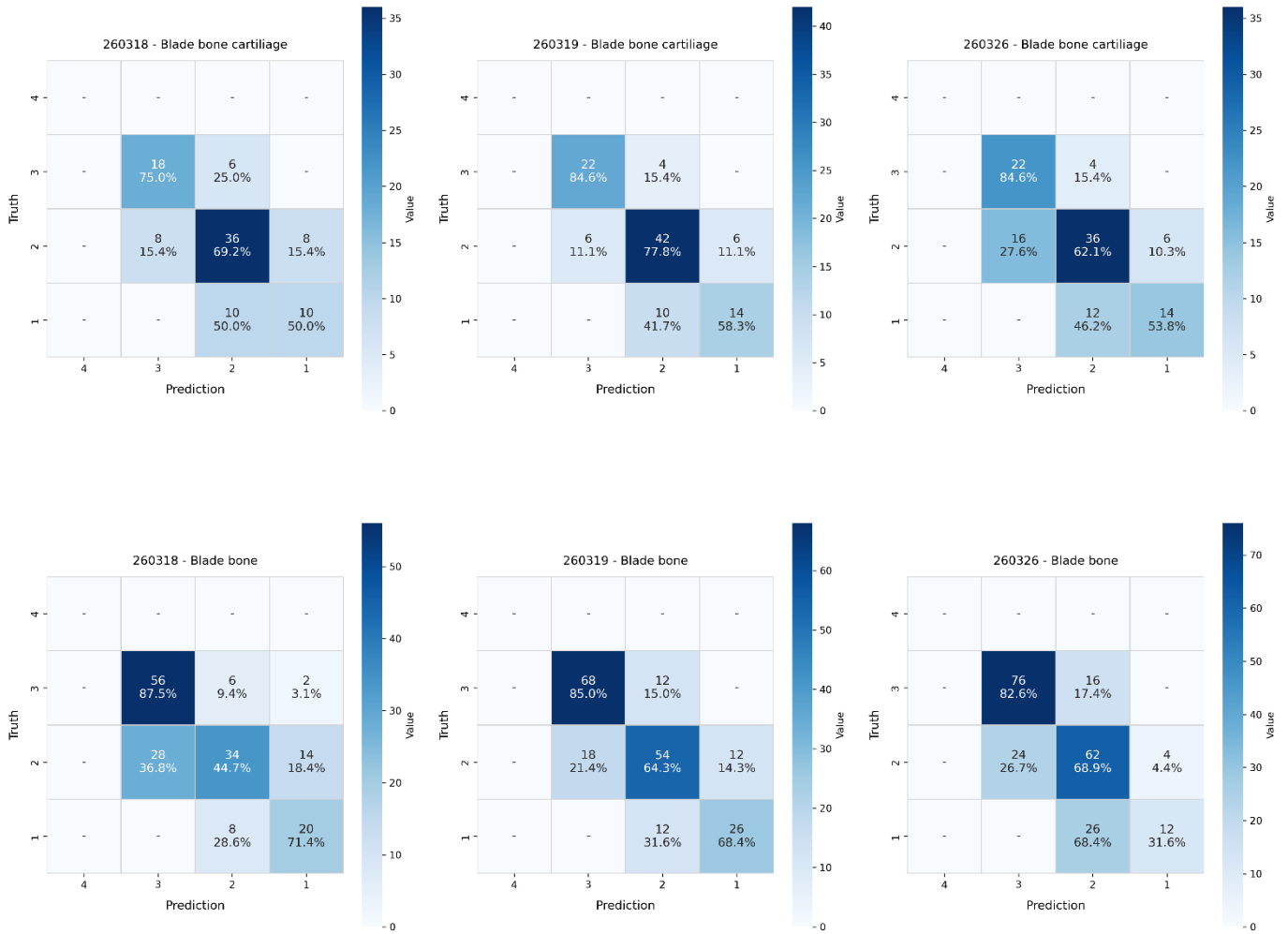
12.2 Bone types used

The list below shows the bone segments actually arriving to the bone belt passing the camera, and the groups it was necessary to separate them in for recognition.

Danish name	English name
Haleben nøgleben	Backbone aitchbone
Pistol Rygben (Højreb)	Pistola Back bone ("Full rib)
Pistol Rygben (Tyndsteg Højreb)	Pistola Back bone ("Short loin)
Pistol Blandet	Pistola Miscellaneous
Pistol Rørben	Pistola Femur Bone
Pistol Skankeben	Pistola Shin Bone
Wing Blandet	Wing Miscellaneous
Wing Bovblad	Wing Blade Bone
Wing Brystben	Wing Sternum
Wing Brystben ribben	Wing Sternum ribs
Wing Fjederben	Wing Soft bone
Vinge Fjederben ribben	Wing Soft boneribs
Vinge Genik	Wing "Genik" Atlas
Vinge Halsben	Wing Neckbone
Vinge Halsben (bag side)	Wing Neckbone (back side)
Vinge Ribben	Wing Ribs
Vinge Rygben	Wing Backbone
Vinge Rygben (bag side)	Wing Backbone (back side)
Vinge Rørben	Wing Femur Bone
Vinge Skankeben	Wing Shank bone

12.3 Confusion matrices for trim level models





12.4 Dashboard views

Bone Yield Dashboard

Dates



PREVIOUS

LATEST

NEXT

WEEK

LAST WEEK

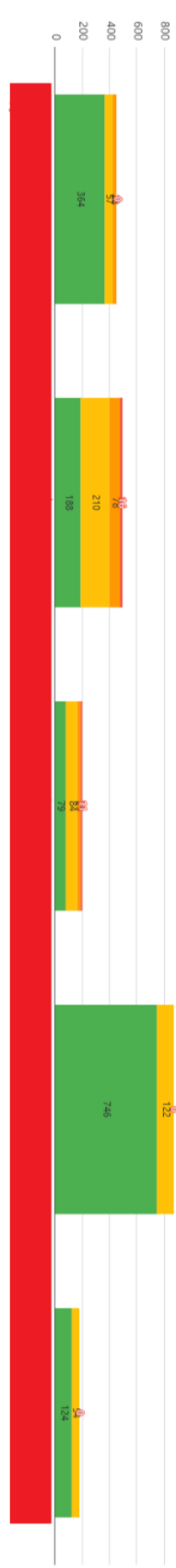
TWO WEEKS

MONTH

2186 Items /

OVERVIEW GRADE TIMELINE FILES

Count



Product	Grade 1	Grade 2	Grade 3	Grade 4	Total
TOTAL					

Bone Yield Dashboard

Date: [REDACTED]

- PREVIOUS
- LATEST
- NEXT
- WEEK
- LAST WEEK
- TWO WEEKS
- MONTH

3864 items / [REDACTED]

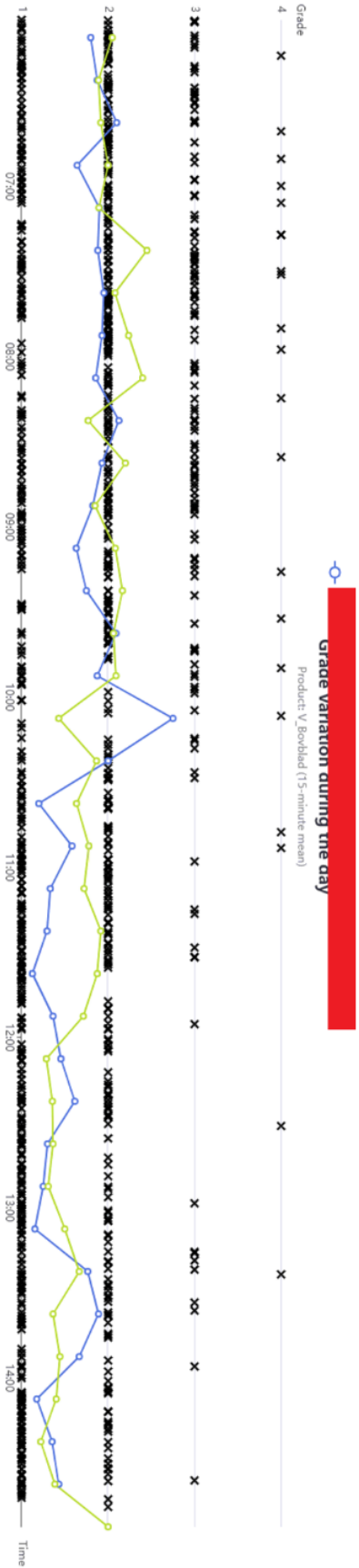
- OVERVIEW
- GRADE TIMELINE**
- FILES

Grade timeline

Bucketed grade summary by time of day, with optional raw scatter overlay

- P_RYGBEN(TVNDSTEG)
- V_BOVBLAD**
- V_BOVBLADSRUSK
- V_HALS BEN
- V_RYGBEN

Window (minutes): 15 Aggregate: Mean Show raw scatter



Bone Yield Dashboard



Dates



PREVIOUS

LATEST

NEXT

WEEK

LAST WEEK

TWO WEEKS

MONTH



OVERVIEW



GRADE TIMELINE



FILES

2186 Items /



ALL	P_RYGREN(TYNDSTEG)	V_BOVBLAD	V_BOVBLADSRUSK	V_HALSBEN	V_RYGREN
Day	Time	Product	Quality	Cont %	
2026-06-06	09-060114.1	V_Bovblad	Q1	96.8	
2026-06-06	09-060127.1	V_Bovblad	Q2	77.2	
2026-06-06	09-060132.6	V_Bovblad	Q3	98.5	
2026-06-06	09-060152.6	V_Bovblad	Q3	99.4	
2026-06-06	09-060204.1	V_Bovblad	Q3	95.5	
2026-06-06	09-060226.6	V_Bovblad	Q1	80.2	
2026-06-06	09-060301.6	V_Bovblad	Q2	99.7	
2026-06-06	09-060418.1	V_Halsben	Q1	99.6	

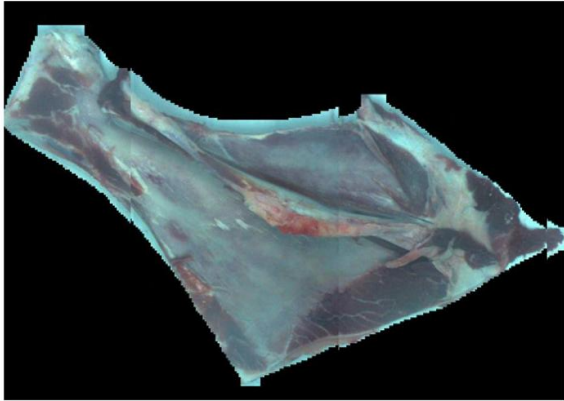
Bone Yield Dashboard

Dates: 2026-06-08, 2026-06-09, 2026-06-10
Mon 8 Jun → Wed 10 Jun

Showing 1426 of 5860 items

ALL P_RYGBENT(TYNDSTEG) V_BOVBLAD

V_Bovblad - Quality 1



Timestamp: 2026-06-08 14:26:00

Product ID scores:
V_Bovblad: 99.5%
Blander_kodstykker: 0.2%
Blander: 0.1%
V_Ribben: 0.1%
V_Ryghen_Halsben_Back: 0.1%

Quality scores:
Grade 1: 59.4%
Grade 2: 38.4%
Grade 3: 2.0%
Grade 4: 0.2%

1426 items / 3 day(s)

Conf %	Count
99.9	1
96.2	1
99.5	1
100	1