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AI-BASED HAM CONFORMITY GRADING

Björn Böken[1*]

[1] CSB-System SE, Geilenkirchen, Germany

*Corresponding author email: bjoern.boeken@csb.com

I. INTRODUCTION

One of the main aims in non-vertically integrated pig breeding is maximizing the final fattening weight to receive a maximum payoff from the slaughterhouse. Conversely, slaughterhouses try to maximize the slaughter exit yield, mostly influenced by weights of the valuable main parts only, while they simultaneously try to minimize the pig weight [1, 2]. Today, pigs in most parts of Europe are therefore classified based on the SEUROP grading scheme, which is computed from each pig's lean meat percentage (LMP).

While SEUROP-based / LMP-based payments are a reasonable compromise, they still do not necessarily well express the pig's lean meat distribution [2, 3]. For instance, there are pigs that have a relatively high lean meat percentage, but an average or bad ham. Consequently, slaughterhouses try to introduce additional measurements as early as possible in the process chain to better assess the slaughter exit yield of each individual pig. They integrate these assessments directly into the payment process. One example is a ham conformity measurement, which is particularly useful to identify pigs with well-shaped hams as one of the most valuable parts. Considering this, the main aim of this work is to develop an automatic ham grading solution.

II. MATERIALS AND METHODS

A slaughterhouse in Belgium, where manual ham conformity grading is already in place, was used as a reference to identify the ham shape. In addition, an existing machine vision solution to automatically recognize the pig sex by means of AI / deep learning technologies was used [4], which also detects and analyzes the ham region in the process.

As a first experiment, the existing manual ham conformity grading according to six conformity classes (EE, E, AA, A, B and C) [5], in combination with 8913 images acquired during the real process, were used as a reference. The data were joined by means of RFID tags and were used to directly train a deep learning neural network as a preliminary evaluation, i.e. without any kind of postprocessing, cleaning or verification of the ham gradings. However, the results indicated that this manual reference is not sufficiently standardized, details are omitted for space constraints.

Since the existing data was not directly usable, an alternative strategy was applied. Here, two human meat experts (certified grader, butcher) jointly analyzed images acquired on three days to create a reference data set containing a representative, good selection of ham conformity classes. By manual sorting, a data set consisting of 629 images was created: 101 AA, 196 A, 177 B and 155 C. The rare classes EE and E, which apply to less than 1 % of Belgium pigs, were ignored. An extension for those is planned, but requires respective data, too.

Next, the data were used to train and evaluate a deep learning neural network to implement fully automatic, standardized ham conformity grading solution integrated into the slaughter line.

III. RESULTS AND DISCUSSION

The model was trained for 200 epochs, i.e. full iterations over the whole training data. The actual training data were created using a random, stratified 80% / 20% split to use 20% as independent test data. This approach was repeated 20 times to generate average / standard deviation statistics. The respective results are summarized in Table 1 and Figure 1, respectively.

On the left-hand side of Figure 1, the running training accuracies with standard deviations are illustrated. Additionally, the respective validation accuracies are presented on the right-hand side of Figure 1. They were computed every five epochs. Most importantly, after finishing 200 epochs, the trained model reaches a running training accuracy of 91.5 % ± 3.8 % and a validation accuracy of 77.4 % ± 4.4 %, respectively, each averaged over 20 iterations.

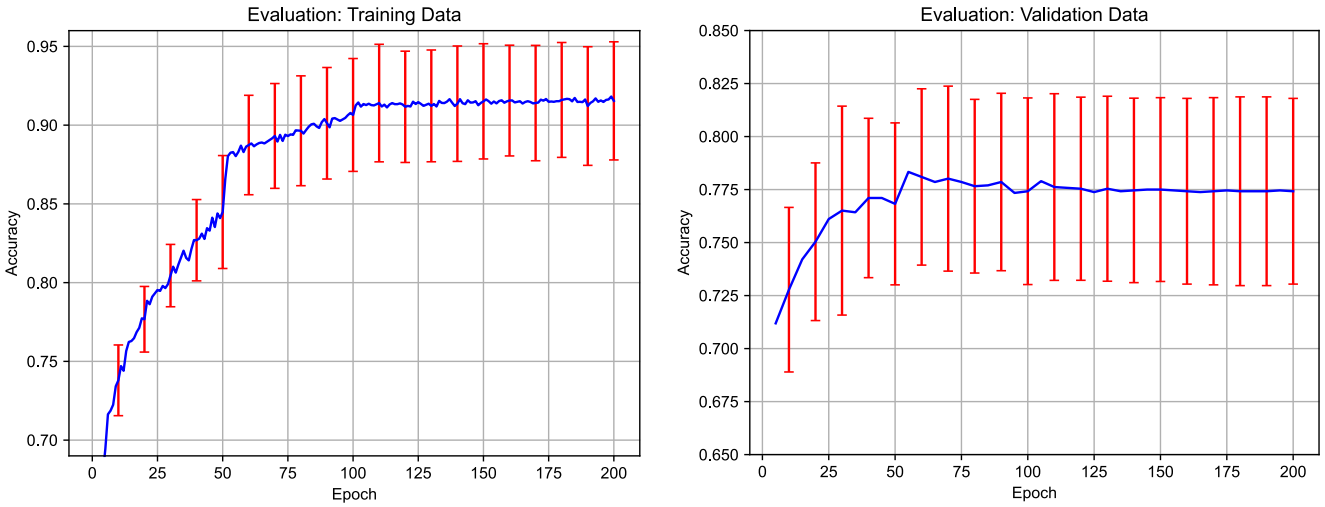


Figure 1. Accuracies of predicting the ham conformity class. Running training accuracy per epoch as well as validation accuracies illustrate the model's convergence.

	AA	A	B	C
AA	16.35 ± 1.8	3.65 ± 1.8	0 ± 0	0 ± 0
A	3.3 ± 1.7	31.4 ± 2.4	4.05 ± 1.7	0.25 ± 0.4
B	0 ± 0	5.25 ± 1.7	24.85 ± 2.6	5.9 ± 1.7
C	0 ± 0	0.25 ± 0.4	5.8 ± 2.4	24.95 ± 2.2

Table 1. Average confusion matrix computed over 20 iterations. Each entry describes the number of respectively classified images on average.

As accuracy statistics do not capture the error distributions, Table 1 presents the average confusion matrix. Here, entry *i* in column *j* contains the number of validation images from class *i* that are classified as *j*. Therefore, the diagonal contains the correct classifications, whereas the remaining entries correspond to errors. These were computed for each iteration. Table 1 presents the average and standard deviation. The most important observation is that the prediction is either correct or off by one class in more than 99 % of the time.

IV. CONCLUSION

In summary, the results are promising. The correct class is identified with a validation accuracy of 77.4 %, whereas most deviations are off by a single class only. On the other hand, due to the lack of sufficiently standardized grading criteria, any reference unavoidably remains slightly arbitrary.

While establishing a more standardized reference, a reasonable aim is to use continuous scores instead of discrete classes because there is no strict boundary between two grades. This data would allow to train regression models instead of the current classification model, which could be more useful for the actual task. We will try to verify the validity of the automatic measurement during the Dutch dissection trial taking place in 2025.

REFERENCES

Papers:

1. Spiller, A., Theuvsen L., Recke G., Schulze B. *Sicherstellung der Wertschöpfung in der Schweineerzeugung: Perspektiven des nordwestdeutschen Modells*, Georg-August-Universität Göttingen, Göttingen, 2005. URL: https://www.uni-goettingen.de/de/document/download/c0abf0f113282317197698233 89d65f9.pdf/Gutachten%20SWL%202005_gesamt.pdf
2. Brade, W., Flachowsky G. *Schweinezucht und Schweinefleischerzeugung: Empfehlungen für die Praxis*, Bundesanstalt für Landwirtschaft und Ernährung, Special Issue 296, 2006. URL: https://literatur.thuenen.de/digbib_extern/bitv/zi040827.pdf
3. Niemann, C. *AutoFOM 3: Jetzt noch genauer sortieren!* In: TopAgrar 3, 2014, URL: https://www.topagrar.com/schwein/aus-dem-heft/autofom-3-jetzt-noch-genauer-sortieren-9667709.html
4. Böken, B., Dennemann, R., Kasel, A. *Fully automated deep learning-based sex recognition in pigs* In: Fleischwirtschaft International 3, 2021.
5. Vlaamse overheid Departement Landbouw en Visserij *Evolutie van de indelingsmethoden van varkenskarkassen* URL: https://www.varkensloket.be/Portals/63/Documents/evolutie_van_de_indelingsmethoden_van_varkenskarkassen.pdf