O-05-03

Artificial intelligence (AI) and vision technology for improving efficiency and quality in meat production (#621)

Holger Dirac, Peter Stentebjerg, Glenn B. Nielsen, Troels T. Mørch

Danish Technological Institute, DMRI, Taastrup, Denmark

Introduction

AI is receiving increased attention as a potential game changer within several diverse areas such as medicine, law, security, and marketing. The rapid progression of new AI applications is not just due to advancement within computer science, indeed to a large extent the basic approaches and algorithms have been available for decades. It is the availability of vast amounts of digitalized data, e.g. from the Internet, and the ever-increasing performance of hardware that lie at the foundation of the development. Within production and specifically within food and beverage there is also an increasing awareness of the AI potential. We have investigated the potential of AI in combination with vision for several different applications within meat production. The applications center around food sorting, quality assurance, production technology (e.g. robotics), and maintenance. The common driver for introducing AI technology in meat production is the need to embed expert knowledge into software to be able to automate complex processes. Combining vision technology with deep learning image analysis for classification, feature recognition, and anomaly detection is a powerful tool to achieve this objective.

Here we report the results of a network trained to classify meat products according to product type, i.e. for automatic product recognition and destination in the plant. In the cutting plant this task is normally performed by a skilled operator who is familiar with the different types of main and by-products, which are produced on the de-boning line. Crates with product are transported to a weighing station with a data terminal where the operator identifies the product in the crate, assesses the quality and enters the product identity number into the system.

Methods

Deep learning architectures, such as convolutional neutral networks, are based on artificial deep neural networks and can be used to analyze images, i.e. for computer vision. An artificial neural network performs a numerical analysis using weights that are adjusted for the given application. The adaptation of these weights for the application is referred to as training of the network and is usually performed with a numerical optimization. Traditionally, expressive features in the data are extracted and the network trained by adjusting the weights to give reasonable predictions based on these features. By increasing the depth and width of the network it becomes able to capture more complex relations and therefore "deep" models generalize better than traditional "shallow" artificial neural networks. As a consequence there is less need for dedicated feature extraction but instead the network is applied to the raw data (images) and learns to extract the relevant features through training.

In the reported application images were grouped into 30 categories that covered 90% of all products produced at the site. Each category was based on visual distinction. A model based on the ResNet50 architecture was trained on 700 images of each category. An additional 300 images were used in the offline testing. Finally, the network was implemented in an online version, which recognizes the product type in real time. The online version ran for 10 working days identifying 30.000 images, this data was validated against the manual operator.

Results

The automatic product recognition system had a precision of 97% when tested off-line on the annotated test set. Precision refers to the percentage of all test images assigned to the correct category. The prediction of a class from such a network is based on a numerical result, this result also refers to a certainty in the prediction. Thresholding the prediction, so the uncertain samples were routed for manual inspection, a precision of 99% could be achieved on the test sample with manual handling of only 7% of the cases.

The online version had a precision of 94% when using the operator identification as the truth. The performance could be improved to 98% if a system similar to the one discussed above was implemented. In this case 11% would be sent for manual inspection. When validating the online system against manual operators the error rate of manual recognition must be taken into account. To quantify this, two operators were benchmarked against each other. The operators were in accordance with each other in 85% of the recognitions when identifying product types from images.

Conclusion

AI, specifically deep learning in combination with vision technology, is a powerful tool in meat production were the further automation of processes requires embedding expert knowledge into information and control systems. Specifically, we have shown that a neural network system can largely automate product recognition and destination in the plant thus reducing operator cost and at the same time potentially decreasing the number of erroneously identified products.

Notes

AI vision system
DynaCQ vision platform used for collecting images of different product types. An online version of product recognition was subsequently implemented in the platform.

Notes