Determining Desirable Swine Traits that Correlate to High Carcass Grades for Artificial Intelligence Predictions

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Abstract.

With the global population continuing to grow, there has been an increased stress applied to the agriculture industry to improve efficiency and yield. It is important to recognize that the livestock industry has the additional pressure of not only producing more product but also ensuring that the consumer will be satisfied with flavor after purchasing. In the swine industry various decisions are made throughout an animal's life to ensure that it will result in a desirable carcass while keeping reasonable feed intake. After a hog has gone to market and been processed it goes through a variety of grading systems to quantify the worth of the product. Yield grades, carcass grades, and fat free lean calculations are some of the methods used to determine product worth. However, these determinations cannot be made until an animal has been processed as each method works to describe the carcass. Artificial intelligence (AI) has become an increasing presence in agriculture and is expanding its role into the realm of livestock. The capabilities of AI models have been steadily increasing and a new realm of image-based systems are cropping up. Some of the market characteristics that are taken into consideration in pork carcass grading can be seen in the live animal. Thus, a model would be able to predict how an animal grades at market without having to go through processing. The ability to make these predictions ahead of time would allow for producers to tailor breeding and feeding decisions to best support the operation. The integration of AI within the market sector would also speed up the process of grading within plants. If predictions were made prior to processing, then carcass grading could become a confirmation of the original assessment and not require as intense scrutiny. It is also prudent to confess that the current grading system is reliant on subjective decisions allowing AI to present a solution in the manner of removing some human bias.

Keywords.
Swine, Pork, Carcass Grading, Artificial Intelligence

Introduction

The pressure being placed on the agriculture industry has a direct correlation to the growth that the global population is experiencing. All components within the agriculture industry have been tasked with increasing their yields and efficiencies. This pressure has an additional component within the realm of livestock production, as producers must also ensure they are creating appealing food products for customers. According to the United States Department of Agriculture (USDA) the United States is the third-largest producer and consumer of pork in the world (Haley, 2024). Within the United States pork is the third most eaten protein, falling in line behind chicken and beef consumption (Blazejczyk, 2023). In the swine industry producers attempt to balance cost of feed with the return that will come from the processing of the animal. This causes producers to select for animals that have higher feed efficiencies, which is the calculation of pounds of food required to add a pound of muscle.

If producers could predict carcass grades on a live animal, they could then tailor care, feed, and market timelines to maximize profitability at processing. Artificial intelligence (AI) may be the key to unlocking this next shift in the market industry. While AI models are proving to be powerful, the timeline to higher predictive accuracy can be reduced by focusing the model on specific traits. Therefore, the objective of this work is to determine those swine traits most closely linked to carcass grading that can also be observed in the animal phenotype. These traits will then be used to train an AI tool to live carcass grade swine prior to shipping to market.

Background

When a market hog has reached its final stages of growth it is sent to a processing plant where the carcass is harvested. At the processing plant a carcass will be observed by a trained USDA inspector who ensures the quality of the product and can also bestow grades. The quality inspection is focused on the experience a consumer will have when cooking and eating the meat product. The traits that are considered during the inspection include color, firmness, water holding amount, marbling, and texture (Shircliff, 2016). After the carcass has passed the quality inspection it can be graded, however it is worth mentioning that carcass grading is not common practice at most processing plants as it would slow down the speed at which the line can operate (Shircliff, 2016).

The quality grading systems do vary from country to country, however the characteristics that are considered in these gradings remain the same. In the United States processing plants have adhered to USDA grading standards since 1931, though the current set of standards were approved in 1985 (USDA, 1985). There are five classes of carcasses: barrows, gilts, sows, stags, and boars however carcass grades are not given to the stag and boar classes (USDA, 1985). These USDA carcass grade standards vary according to the sex and age of the hog going into market as age and intact reproductive organs affect the quality of the meat product for the consumer. This paper will focus on the standards that apply to the barrow and gilt carcass classes as they better represent the ideal market product.

There are two general considerations when grading barrows and gilts these are quality of the carcass and expected yield of the four lean cuts ham, loin, picnic shoulder, and Boston butt (USDA, 1985). The quality consideration as mentioned above is focused on the consumer experience. The loin cut is most commonly used to determine quality based upon its marbling, color, and firmness. When undergoing the quality check external fat is not considered aside from ensuring that there is enough belly fat present for bacon production (USDA, 1985). Once a carcass has passed a quality inspection it may move on to be graded. To predict amount of lean meat, backfat thickness is measured, as a higher amount of external fat has a negative correlation to the amount of lean present. Backfat thickness, including skin, is measured over the last rib in inches (USDA, 1985). Next a degree of muscling is determined by subjective evaluation of muscle thickness related to skeletal size. The ham cut is most often used to determine degree of muscling as it is least affected by fatness (USDA, 1985). When an animal fattens, the fat accumulates from head to tail, so while the ham may have internal fat there is minimal external fat influencing the muscling score. Equation 1 (USDA, 1985) is used to determine pork carcass grade:

$$\text{Carcass grade} = (4.0 \text{ X backfat thickness, inches}) (1.0 \text{ X muscling score}) \quad (1)$$

Pork carcass grading is a complex process that requires standardized methods and a deep understanding of the traits that contribute to the carcass's economic value. The literature suggests a movement towards a more comprehensive grading system that can adapt to changing market needs and production methods.

Artificial Intelligence has gained an increasing presence in agriculture through the multitude of sensors used by crop farmers. This technology is beginning to expand into the realm of precision livestock (Chase et al., 2006). Imageomics specifically is the use of computer vision and analyzing capabilities to further break down traits within an image. The computer capabilities allow for unique perspectives that were previously unattainable. The use of AI and Imageomics within the swine market industry would allow for carcass grade predictions to be carried out on the live animal, while also reducing human bias.

Currently, the role of AI in the industry has been explored within animal health, welfare, and the ability to detect estrus cycling in cattle (Wongvivatvaitaya et al.; 2023, Heald et al., 2000). Within the realm of animal health AI has been used to predict with an up to 84% accuracy mastitis diagnoses within a herd (Heald et al., 2000). Regarding animal breeding, AI has been used to detect estrus cycling so that artificial insemination can be properly timed (Wongvivatvaitaya et al., 2023). This role of AI is intriguing as it would also work to increase yield, as it allows farmers to breed within a more fertile window which results in higher pregnancies from a single breeding cycle. The market industry has begun to implement AI into processing plants to increase efficiency when packaging meat cuts (Marble Technologies, 2024). These AI projects, while innovative still leave the data from phenotypes untouched.

It has long been accepted that phenotype is equal to the genetic potential of an animal plus the environment the animal was raised in. Equation 2 is used to represent the relationship between animal genotype and environment.

$$\text{Phenotype} = \text{genotype} + \text{environment} \quad (2)$$

This environment can include aspects such as nutrition available, physical environment, injury, and physical activity. The newest role that AI has slipped into within the livestock industry is animal phenotyping, as it offers innovative ways to measure and analyze traits. This technology not only enhances the accuracy of phenotyping but also promises to transform animal breeding and health research.

Conservation biology has begun to bridge this gap, using AI to study behaviors of rare species. Zuffi et al. (2019) outlined a computer model that was able to predict the 3D pose of a Grevy's zebra, an endangered species, when it was given a 2D photograph of the animal. This study demonstrates that AI models can be used to extract various datapoints within and image and makes predictions. The livestock industry focus on genomics has begun to shift as a multitude of sensors available on the market allow for collection of phenotypic traits to be collected in large amounts. Artificial intelligence, particularly machine learning, plays a crucial role in interpreting the complex data in turn allowing for more accurate animal phenotyping. Animal breeding and selection decisions will be revolutionized by the precision livestock technologies as the continuous collection of traits increases (Pérez-Enciso & Steibel, 2021). Morota et al. (2022) highlight the importance of AI in accelerating phenotyping efforts in animal breeding. They emphasize the development of computer vision and wearable sensors which provide non-invasive, high-resolution measurements of animal body mass and behaviors. These technologies are instrumental in connecting animal phenotype with pedigree and genetics, thus driving genetic advancements.

While AI shows a strong promise in the world of animal phenotyping there are some challenges that must be taken into consideration. One of the main challenges is the lack of homogeneity and gaps within the data collection which can create complications within AI model development. This incomplete data can require penalization or dimension reduction which leads to statistical and computational issues (Pérez-Enciso & Steibel, 2021). The review by Neethirajan (2023) broaches the potential technical, economic, and ethical challenges that arise from implementation of digital phenotyping platforms. This includes the development of 'digital twin' for genomic research and behavior monitoring, while promising, presents significant hurdles with technology adoption and ethical considerations (Neethirajan, 2023). Another challenges that AI presents is the need for an interdisciplinary research team. Knowledge from fields such as veterinary medicine and computer sciences are needed to implement AI-based methods when assessing animal behavior and welfare. This interdisciplinary approach is essential for developing and adapting AI methods to gain accurate and continuous monitoring of animal welfare indicators (Giersberg, 2024). The last challenge of expensive phenotyping equipment and proprietary or incompatible data formats is beginning to be addressed by open-source devices and tools. However, adoption of AI technologies is still a challenge due to the need for standardization and integration into existing systems (Nabwire et al., 2021). Knowledge of these challenges allows for efforts to be made to solve them as AI technologies continue to advance.

Discussion

Across the literature and the USDA standards there are some notable swine traits that link into the grade given to a carcass. The most well noted trait is the amount of backfat a carcass has which is seen by its explicit use in the carcass grade formula given in Equation 1. Other traits that appeared frequently throughout the literature include hot carcass weight, loin eye area, body length and depth. These traits are all in reference to the carcass itself however they do have equivalent traits that can be found on the live animal.

Within the live animal body weight can fill the role of hot carcass weight. Loin eye area can be replaced with length and depth of loin which can be roughly measured on a hog by handling. Degree of muscling can still be viewed by relation of the size of the ham to the animal. Backfat while being the most important trait would be the most difficult to estimate on the live animal but not impossible. As animals fatten from front to rear it should be possible to estimate external fat based on its accumulation in other areas on the body such as the jowls.

Artificial intelligence and Imageomics are models that can learn and improve as more information is fed to them so it is not out of the realm of possibility that these models may find traits on the live animal phenotype that researchers had not yet considered. This research aims to test the strength of AI in comparing these known and unknown traits on the live animal to predict how it would grade in a market setting.

Conclusion or Summary

Artificial Intelligence (AI) is a growing presence within the agriculture and more specifically market industries. Processing plants can now be found using AI to identify cuts of meat so they can be properly packed. The next step is clear, AI will allow for predictions of market quality while an animal is still alive. Utilizing images with preidentified areas of interest such as back fat, body depth, body size, will allow for an AI model to be trained rapidly for more accurate predictions. The next step of this research is to work on building a model for carcass grade predictions.

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