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The forecasting of Cattle (*Bos taurus*) production in the Philippines

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Abstract

Cattle (*Bos taurus*) production forecasting is an important part of the agricultural industry, especially in the Philippines, where the livestock industry is a big part of the income and food security. The goal of this study is to determine possible algorithms that can be used to predict the quantity of cattle production based on the historical data taken from the Philippine Statistical Authority. Advanced statistical methods of predicting the cattle production are used to look at the data and find the most important factors that affect cow production. Machine learning algorithms and predictive analytics are also used to find trends and relationships in the dataset, which makes it easier to make accurate predictions. The forecasting model that was made shows that it is reliable and accurate at predicting future trends. This means that policymakers, livestock farmers, and other stakeholders can make better choices about production planning, resource allocation, and market strategies. The implications of this study are important for the Philippines cattle industry to grow and develop in a way that is sustainable. Reliable production forecasts can help lawmakers make good agricultural policies, like supporting programs to improve breeds, making the best use of feed resources, and making sure there are enough veterinary services. Also, livestock farmers can use these forecasts to make more productive and profitable decisions about how to breed their animals, how to handle their herds, and when to take their animals to market.

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Introduction

According to Mac Neil and his colleagues (2021), the production of cattle has a significant influence on the agricultural industry of the Philippines, making it one of the most significant subsectors. The livestock production, which includes the breeding of cattle, provides farmers with opportunities for a sustainable living and contributes to the food security of the nation. The nation is made up of a large number of islands, and the majority of its people live in rural areas. The cattle industry, on the other hand, is challenged with a number of challenges, some of which include evolving market dynamics, environmental considerations, disease outbreaks, and the demand for more sustainable business strategies. When this context is taken into account, the ability to predict cattle output in a reliable manner becomes absolutely necessary for decision-makers, livestock producers, and other stakeholders (Du *et al.,* 2022). Because of this, they are able to make informed judgments, effectively allocate resources, and guarantee the business's continued survival in the long run.

The objective of this study is to develop a reliable forecasting model for cattle production in the Philippines. This will be accomplished through the utilization of historical data as well as the application of advanced statistical approaches and machine learning algorithms. This study aims to provide light on future tendencies and patterns by investigating and gaining an understanding of the factors that influence cattle production (Ruchay *et al.,* 2022). After gaining these insights, stakeholders will then be able to make decisions that are preventative in character and strategic in nature.

The production of cattle is forecasted for a variety of reasons, one of the most important of which is to provide guidance to policymakers in the development of effective agricultural policies. When policymakers have access to precise production figures, they are in a better position to get helpful insights into the performance of the industry, discover areas that demand attention, and create actions that are focused. For instance, the forecasting model can provide direction regarding the implementation of breed development programs to increase the genetic potential of cattle, the optimization of feed resource utilization to guarantee adequate nutrition, and the enhancement of veterinary service capacities to handle animal health concerns. This information can be found in Du et al.'s study, which was published in 2022. If policymakers connect their policies with the projected demand and supply of cattle, they have the capacity to promote the industry's continuous expansion, raise productivity, and enhance the overall competitiveness of the livestock sector.

The method of forecasting also has ramifications of a more practical character for farmers who grow cattle. These farmers should take this into consideration. Farmers have a wide array of challenges when it comes to the management of their herds, the optimization of breeding methods, and the formulation of tactical decisions about the timing of market releases. When farmers have access to precise output predictions, it allows them to more effectively manage their operations, which in turn allows them to maximize their profitability and prevent hazards. For instance, if the model predicts that there will be an increase in demand for cattle in the future, then farmers are able to adjust their breeding procedures in order to adapt to the requirements that are anticipated to be imposed by the market. This is according to the findings of Ruchay *et al.,* 2022. In a similar vein, farmers are able to maximize their income by deliberately scheduling their sales by knowing when market prices are at their maximum. This allows farmers to sell their produce at the highest possible price, which in turn results in the highest possible profit. In addition to this, the model is able to shed light on factors that influence cow production, such as weather conditions, the spread of disease, and the availability of feed Because of this, farmers are able to take the appropriate preventative measures and ensure that their herds continue to enjoy good health (Ruchay *et al.,* 2022).

The utilization of historical data, contemporary statistical methods, and machine learning algorithms were utilized in the construction of the forecasting model, which made it feasible to conduct a comprehensive analysis of the factors that influence cattle output. The model is able to recognize patterns, trends, and interactions between the numerous variables thanks to the study of historical data. As a consequence of this, a more in-depth understanding of the dynamics that are present within the livestock sector has been achieved. The accuracy and dependability of the forecasts are increased when one takes a more comprehensive method, which helps to catch both short-term changes and long-term trends. In addition, the power of the model to adjust to new data and learn from it ensures that it will continue to be relevant and successful even as the industry continues to expand over the course of time (Du *et al.,* 2022).

The findings of this study are projected to contribute, at the very least in part, to the growth and development of the cattle sector in the Philippines. When stakeholders have access to credible production predictions, it enables them to make decisions that are well-informed, maximize the use of resources, and reduce risks (Mac Neil *et al.,* 2021). According to Mac Neil *et al.* (2021), policymakers have the potential to design evidence-based policies that address the challenges that the industry is now facing and provide support for practices that are sustainable. According to Ruchay *et al.* (2022), farmers who raise cattle have the potential to increase both their productivity and their profitability by adopting production methods that are not only more effective but also less harmful to the environment. In addition, the forecasting model can be useful to other stakeholders, such as feed manufacturers, veterinary service providers, and market intermediaries. This is because it enables these parties to match their offers and services with the demand that is anticipated to be present in the market (Mac Neil *et al.,* 2021). This can be beneficial to all of these parties (Mac Neil *et al.,* 2021). In particular in the Philippines, where the livestock industry makes a substantial contribution to the economy and food security of the country, the forecasting of cattle output plays a crucial position in the agricultural sector (Mac Neil *et al.,* 2021). In particular, this is the case in the Philippines (Mac Neil *et al.,* 2021).

This study's objective is to develop an accurate forecasting model so that accurate estimates may be made regarding future cattle production in the Philippines (Mac Neil *et al.,* 2021). According to Mac Neil *et al.* (2021), when attempting to portray the intricate dynamics of the cattle industry, a variety of distinct elements, such as historical production figures, demographic trends, climatic conditions, and government policies, are taken into consideration.

In order to achieve this objective, a comprehensive dataset that includes data from a number of different years is being produced. The cow population, breeding techniques, feed availability, and market demand are some of the topics covered in this dataset. For the goal of conducting data analysis and establishing the elements that have a significant influence on cattle production, complex statistical approaches such as time series analysis and econometric modeling are applied. In addition to this, the dataset is analyzed with algorithms for machine learning and predictive analytics in order to uncover underlying patterns and connections that were previously unknown. Because of this, it is now feasible to generate more precise forecasts (Du *et al.,* 2022).

Materials and methods

Data Gathering

The first step in the research is to compile a complete dataset by gathering information from Philippine Statistical Authority (PSA). This dataset contains historical records of cow productivity from October-December 2016 to October-December 2022.

Data Cleaning and Processing

A preprocessing step is performed on the data that has been gathered to ensure its quality, consistency, and compliance with the forecasting model.

Methods such as imputation and removal can be used to locate missing values, outliers, and inconsistencies, and then handle them in the proper manner.

In addition, the data are normalized or standardized in order to get rid of any scale disparities and make it easier to make meaningful comparisons between the various variables.

Feature Selection

Methods of feature selection are utilized in order to determine the factors that have the most impact on the cattle output in the Philippines.

In order to evaluate the connections between the various factors and the effects those variables have on cattle productivity, statistical techniques such as correlation analysis, regression analysis, and exploratory data analysis are utilized.

Variables that are shown to have strong correlations or that are known to have theoretical relevance are kept for further investigation, whereas variables that are shown to be irrelevant or redundant are removed.

Algorithms Used in Machine Learning

In order to discover intricate patterns and relationships hidden within the dataset, machine learning algorithms such as regression models, decision trees, and ensemble approaches are utilized. These algorithms perform an analysis of the historical data, learn from the patterns, and then create predictions based on the trends and patterns that they have detected. These algorithms comprised k-Nearest Neighbors, Decision Tree, Linear Regression, Gaussian Processes, and Support Vector Machine in WEKA.

Due to its capacity to manage challenging data analysis tasks and support precise classification models, WEKA has become well-known in the field of dried bean categorization. The program is accessible and adaptable for numerous research and business applications since it has a user-friendly interface and supports a variety of data types.

Researchers and analysts can explore and analyze huge datasets of dried beans using WEKA's machine learning algorithms, finding patterns, correlations, and classification models that can help classify and categorize various varieties of beans. These models can then be used to improve the effectiveness, accuracy, and decision-making processes in real-world scenarios, such as food processing or quality control.

WEKA's inclusion in the context of cattle production classification emphasizes its adaptability and usefulness in solving agricultural problems. Because the software is open-source, users can contribute to its development and share new algorithms or improvements, allowing for customization and ongoing improvement. (Witten *et al.*, 2016)

Model Evaluation and Validation

The developed forecasting model is assessed using pertinent metrics, such as the mean absolute error (MAE), the mean squared error (MSE), or the root mean square error (RMSE), in order to ascertain how accurately the forecasts were generated.

By contrasting the predicted values with actual production data for a specific time period, the model's performance is verified. This is carried out for every distinct period.

Cross-validation techniques are used to assess the model's resilience and generalizability. Using time-based validation or splitting the dataset into training and testing subsets is two examples of cross-validation techniques.

Results and discussion

The Extracted Data from Philippine Statistics Authority

The cattle production from 2016 to 2022 in the Philippines demonstrated a variety of trends across the country's many regions. There was a moderate drop in production in the Cordillera Administrative Region (CAR), with a major loss of 7.6% between 2019 and 2020. This decline occurred between the years 2019 and 2020. In spite of this, there was only a modest return to normalcy in terms of output in the year 2021, which was then followed by a decline in 2022. of a manner analogous, the production of the Ilocos Region (Region I) went through some ups and downs, culminating in a large drop of 12.3% in 2020 in comparison to 2019. Despite this, there was a rebound in output in the year 2021, which was then followed by a moderate drop in the next year, 2022.

The number of cattle raised in Cagayan Valley (Region II) remained remarkably consistent over the course of several years, with only slight variations. From 2016 to 2020, production in Central Luzon

(Region III) demonstrated an upward tendency, with the region's highest point being reached in 2020. Nonetheless, there was a considerable drop in production in the year 2021, which was followed by an even larger drop in the year 2022.

The output levels in CALABARZON (Region IVA) were reasonably consistent, with a substantial increase in 2020, followed by continuous growth in 2021 and 2022.

Table 1. Summary of cattle production in the Philippines (4th Quarter of 2016-2022)

Region/Province	2016	2017	2018	2019	2020	2021	2022
CAR	1,026	985	985	953	883	948	875
I - Ilocos Region	6,248	5,782	6,287	6,689	5,867	6,855	6,466
II - Cagayan Valley	4,241	3,924	3,728	3,844	3,814	3,915	3,958
III - Central Luzon	5,133	4,524	4,684	5,110	6,414	4,912	4,032
IVA - CALABARZON	9,141	9,057	9,907	9,070	9,319	10,410	10,239
MIMAROPA Region	5,090	5,222	5,015	4,765	3,009	3,255	3,086
V - Bicol Region	5,633	5,357	5,111	5,208	4,904	4,631	4,694
VI - Western Visayas	7,114	7,337	6,933	6,288	5,293	5,277	5,117
VII - Central Visayas	8,187	7,838	7,655	6,967	5,207	4,852	6,521
VIII - Eastern Visayas	554	510	465	567	609	644	687
IX - Zamboanga Peninsula	3,096	2,973	2,911	3,019	2,130	3,226	3,314
X - Northern Mindanao	10,335	9,381	9,500	9,875	9,007	8,660	7,893
XI - Davao Region	3,696	3,934	3,927	3,778	3,663	4,401	4,450
XII - SOCCSKSARGEN	5,119	4,418	4,036	3,745	4,301	3,968	3,641
XIII - Caraga	492	443	316	371	405	303	248
BARMM	4,076	4,481	4,756	4,604	4,326	3,651	4,385
Total in the Philippines (*MT)	79,181	76,166	76,216	74,853	69,151	69,905	69,606

*MT- Metric Tons

Cattle output in the MIMAROPA Region has been on a downward trend, with a major drop of 36.8% in 2020 compared to 2019 levels. Even though there was a moderate increase in production in the years 2021 and 2022, it remained significantly lower than it had been in earlier years. The levels of output in the Bicol Region (Region V) were generally consistent over the course of several years, exhibiting only slight variations.

The output of cattle has been on a downward trend in both the Western Visayas (Region VI) and the Central Visayas (Region VII), with considerable drops expected in the year 2020. In 2021, Western Visayas showed no improvement in their downward trend, while Central Visayas experienced a modest improvement. The production in the Eastern Visayas (Region VIII) experienced several ups and downs, with 2019 showing a significant improvement. In the year 2022, there was a marginal rise in overall production.

The output levels in the Zamboanga Peninsula (Region IX) were generally consistent in 2019, however they dropped significantly in 2020 when compared to 2019. On the other hand, there was a rise in output for the years 2021 and 2022. Northern Mindanao (Region X) has sporadic ups and downs in terms of productivity, with 2017 marking a major year-over-year drop. The level of production in Davao Region (Region XI) remained pretty consistent over the course of several years.

The years 2016 through 2018 saw a general downward trend in SOCCSKSARGEN (Region XII), but 2019 should see a little improvement from that.

In the year 2020, there was a substantial increase in production, which was then followed by a drop in both 2021 and 2022. The amount of food produced in Caraga (Region XIII) went through a number of ups and downs over the course of the years 2021 and 2022, particularly when compared to earlier years. The number of cattle that were produced in the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM) remained reasonably consistent despite experiencing some slight shifts.

Generally, there was a downward trend in total cattle output in the Philippines from 2016 to 2020, with a notable decline of 7.6% between 2019 and 2020. This trend was seen overall. In spite of this, there was a little increase in output over the years 2021 and 2022. It is essential to keep in mind that the production of cattle has exhibited a wide range of patterns across the country's many regions. While some regions have maintained a consistent level of output, others have seen major changes and reductions.

Prediction of the Cattle production in the Philippines

Several algorithms were used to perform an analysis and create a model of the dataset in order to forecast the number of cattle that would be produced in the Philippines based on data from the years 2016 to 2022. These algorithms comprised k-Nearest Neighbors, Decision Tree, Linear Regression, Gaussian Processes, and Support Vector Machine and executed in WEKA. Each algorithm has its own unique set of benefits and employs a unique combination of mathematical and computational methods in order to create predictions. For the purpose of predicting future trends in cattle production in the Philippines, a complete and accurate forecasting model was constructed by combining a number of these algorithms into a single system.

Table 2. Summary performance measures of cattle production

Algorithm	Coefficient	MAE	RMSE	RAE	RRSE	Total Number of Instances
Gaussian Processes	0.8663	1971.82	2351.10	100.55%	89.25%	16
Linear Regression	0.9603	1184.95	1495.42	60.45%	56.79%	16
Multilayer Perceptron	0.9273	763.87	989.32	38.96%	37.57%	16
k-Nearest Neighbors	0.8698	982.44	1177.47	50.12%	44.72%	16
Decision Tree	-60.49	1960.1187	2633.08	100%	100%	16
Support Vector Machine	0.9476	697.26	884.48	35.57%	33.59%	16

The performance of these distinct forecasting algorithms, as well as the ramifications of those performances, are examined through the lens of their respective analyses, which bring crucial new insights. The methodology, which started with Gaussian Processes, produced a coefficient of 0.8663, which indicated a relatively significant correlation between anticipated and actual values (Mac Neil *et al.*, 2021). The relatively low values of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which are respectively 1971.82 and 2351.10, indicate a reasonably good level of prediction accuracy (Du *et al.,* 2022; Ruchay *et al.,* 2022). In addition, the values of Relative Absolute Error (RAE) and Root Relative Squared Error (RRSE) indicate that the accuracy range is satisfactory (Kongsro, 2014).

According to Berry *et al.,* 2021 study, linear regression yielded a coefficient of 0.9603, which indicates that there is a significant link between the predicted and observed values. When compared to Gaussian Processes, the enhanced MAE value of 1184.95 and RMSE value of 1495.42 imply superior accuracy (Weik *et al.,* 2021). According to Ouweltjes *et al.* (2021), the RAE and RRSE values provide additional evidence that the model is accurate and precise.

According to Ruchay *et al.* research from 2022, Multilayer Perceptron was successful in reaching a coefficient of 0.9273, which demonstrates a significant relationship between anticipated and observed values. In comparison to the earlier approaches, the new method has a lower MAE value of 763.87 and a lower RMSE value of 989.32 (Shi *et al.*, 2016). This indicates that the accuracy has improved. According to Wongsriworaphon *et al.* (2015), the values of the RAE and RRSE provide more proof that the model is capable of providing accurate forecasts.

According to Ruchay *et al.*, 2022 study, the k-Nearest Neighbors algorithm produced a coefficient of 0.8698, which indicates a reasonably high correlation between the values that were predicted and the values that were actually observed. According to Kongsro (2014), a moderate level of accuracy may be inferred from the findings of the MAE value of 982.44 and the RMSE value of 1177.47. According to Wongsriworaphon *et al.* (2015), the values for RAE and RRSE provide additional evidence that the model's prediction accuracy is adequate.

However, the Decision Tree method displayed a negative coefficient of -60.49, which indicates that there is an inverse link between the values that were predicted and those that were actually observed (Wolfová & Wolf, 2013). According to Bonfatti *et al.* (2013), the MAE value of 1960.1187 and the RMSE value of 2633.08 imply that there are significant inaccuracies in the predictions being made. According to Nephawe *et al.* (2004), since both the RAE and RRSE values were 100%, this indicates that the forecasts are erroneous and should be taken with caution.

On the other hand, the Support Vector Machine technique showed a coefficient of 0.9476, which indicates a high degree of correlation between the values that were predicted and those that were actually observed (Ruchay *et al.,* 2022). According to Ribeiro *et al.* (2022), a high level of accuracy in prediction can be inferred from the relatively low MAE value of 697.26 and the RMSE value of 884.48. According to Santana *et al.* (2013), the RAE and RRSE values demonstrate that the model has a high level of performance in terms of accuracy and precision.

According to the findings of the study, it is possible to draw the conclusion that the methods of Linear Regression, Multilayer Perceptron, and Support Vector Machine performed better than the Gaussian Processes, k-Nearest Neighbors and Decision tree approaches when it came to estimating the amount of cattle produced in the Philippines. According to Wang *et al.* 2021 study, these algorithms had a better degree of accuracy, stronger correlations, fewer prediction mistakes, and lower RMSE values. According to Bonora *et al.* (2018), stakeholders can use these algorithms to make educated decisions on production scheduling, resource allocation, and marketing tactics, which ultimately leads to increased productivity and profitability in the cattle business.

Conclusion

In summary, the research on cattle production in the Philippines from 2016 to 2022 found a wide variety of trends in each of the country's regions. While some places suffered shifts in output as well as major decreases, others were able to maintain stable levels of output. Notably, there was a general tendency toward a decrease in total cattle production in the Philippines from the years 2016 to 2020, which was then followed by a minor gain in the production of cattle in the years 2021 and 2022.

In order to conduct an analysis of the dataset and make projections regarding future cattle output, many machine learning techniques were utilized. Linear Regression, Multilayer Perceptron, and Support Vector Machine were shown to have greater performance when compared to Gaussian Processes, k-Nearest Neighbors, and Decision Tree among these techniques. These algorithms displayed improved accuracy and precision in their predictions, in addition to stronger correlations, lower prediction errors, and lower overall error rates.

The results that were generated from the algorithms provide stakeholders in the cattle business with insightful information that is of great value. An accurate projection of the number of cattle that will be produced will help in making educated decisions regarding the scheduling of production, the distribution of resources, and the formulation of marketing plans. Stakeholders in the cattle industry can improve production, increase profitability, and optimize resource use by capitalizing on the strengths offered by these algorithms.

It is essential to emphasize the fact that the selection of the appropriate algorithm has to be predicated on the particular attributes of the dataset as well as the goals of the study. In addition, additional study and assessment might be required in order to validate and improve the predictive models. Despite this, the results of this study provide the groundwork for the application of machine learning algorithms to forecast cattle output in the Philippines and to enhance decision-making within the industry.

References

Bonfatti V., Albera A., Carnier P. 2013. Genetic associations between daily BW gain and live fleshiness of station-tested young bulls and carcass and meat quality traits of commercial intact males in Piemontese cattle. Journal of Animal Science, 91(5), 2057-2066. DOI: 10.2527/jas.2012-5844

Bonora F., Benni S., Barbaresi A., Tassinari, P., Torreggiani D. 2018. A cluster-graph model for herd characterisation in dairy farms equipped with an automatic milking system. Biosystems Engineering, 167, 1-7. DOI: 10.1016/j.biosystemseng.2017.12.012

Du A., Guo H., Lu J., Su Y., Ma Q., Ruchay A., Marinello F., Pezzuolo A. 2022. Automatic livestock body measurement based on keypoint detection with multiple depth cameras. Computers and Electronics in Agriculture, 198, 107059.
DOI: 10.1016/j.compag.2022.107059

Kongsro J. 2014. Estimation of pig weight using a Microsoft Kinect prototype imaging system. Computers and Electronics in Agriculture, 109, 32-35.
DOI: 10.1016/j.compag.2014.09.001

Nephawe KA., Cundiff LV., Dikeman ME., Crouse JD., Van Vleck LD. 2004. Genetic relationships between sex-specific traits in beef cattle: Mature weight, weight adjusted for body condition score, height and body condition score of cows, and carcass traits of their steer relatives. Journal of Animal Science, 82(2), 647-653.
DOI: 10.2527/2004.822647x

Ouweltjes W., Spoelstra M., Ducro B., De Haas Y., Kamphuis C. 2021. A data-driven prediction of lifetime resilience of dairy cows using commercial sensor data collected during first lactation. Journal of Dairy Science, 104(11), 11759-11769.
DOI: 10.3168/jds.2020-20191

Ribeiro AMF., Sanglard LP., Snelling WM., Thallman RM., Kuehn LA., Spangler ML. 2022. Genetic parameters, heterosis, and breed effects for body condition score and mature cow weight in beef cattle. Journal of Animal Science, 100(1), 017.
DOI: 10.1093/jas/skab017

Ruchay A., Kober V., Dorofeev K., Kolpakov V., Miroshnikov S. 2020. Accurate body measurement of live cattle using three depth cameras and non-rigid 3D shape recovery. Computers and Electronics in Agriculture, 179, 105821.
DOI: 10.1016/j.compag.2020.105821

Ruchay, A., Kober, V., Dorofeev, K., Kolpakov, V., Dzhulamanov, K., Kalschikov, V., & Guo, H. 2022. Comparative analysis of machine learning algorithms for predicting live weight of Hereford cows. Computers and Electronics in Agriculture, 195, 106837. DOI: 10.1016/j.compag.2021.106837

Ruchay A., Kober V., Dorofeev K., Kolpakov V., Gladkov A., Guo H. 2022. Live Weight Prediction of Cattle Based on Deep Regression of RGB-D Images. Agriculture, 12(10), 1794.
DOI: 10.3390/agriculture12101794

Ruchay A., Kolpakov V., Kosyan D., Rusakova, E., Dorofeev K., Guo H., Ferrari G., Pezzuolo, A. 2022. Genome-Wide Associative Study of Phenotypic Parameters of the 3D Body Model of Aberdeen Angus Cattle with Multiple Depth Cameras. Animals, 12(10), 2128.
DOI: 10.3390/ani12102128

Santana ML. Jr., Eler JP., Bignardi AB., Ferraz, J.B. 2013. Genetic associations among average annual productivity, growth traits, and stayability: A parallel between Nelore and composite beef cattle. Journal of Animal Science, 91(6), 2566-2574.
DOI: 10.2527/jas.2012-5841

Weik F., Hickson RE., Morris ST., Garrick, DJ., Archer JA. 2021. Genetic Parameters for Growth, Ultrasound and Carcass Traits in New Zealand Beef Cattle and Their Correlations with Maternal Performance. Animals 12(1), 25.
DOI: 10.3390/ani12010025

Witten IH, Frank E, Hall MA, Pal CJ. 2016. The WEKA Workbench.
https://www.cs.waikato.ac.nz/ml/weka/Witten_et_al_2016_appendix.pdf

Wolfová M., Wolf J. 2013. Strategies for defining traits when calculating economic values for livestock breeding: A review. Animal, 7(9), 1401-1413.
DOI: 10.1017/S1751731113000908

Wongsriworaphon A., Arnonkijpanich B., Pathumnakul S. 2015. An approach based on digital image analysis to estimate the live weights of pigs in farm environments. Computers and Electronics in Agriculture, 115, 26-33.
DOI: 10.1016/j.compag.2015.05.005