FEDERAL UNIVERSITY OF VIÇOSA

ERIKA FERNANDA LOZANO CRUZ

WEIGHT PREDICTION IN WEANING PIGS USING DEEP LEARNING TECHNIQUES

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2024

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Dissertation submitted to the Federal University of Viçosa, as part of the requirements of the Graduate Program in Agricultural Engineering, to obtain the title of *Magister Scientiae.*

Advisor: Ilda de Fátima Ferreira Tinôco

Co-advisors: Robinson Osorio Hernandez
Jairo Alexander Osorio Saraz
Richard Stephen Gates
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Ilda de Fátima Ferreira Tinôco
Advisor

To God and to my Family.

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Everything is possible to one who has faith.

(Mark 9:23)

ABSTRACT

LOZANO CRUZ, Erika Fernanda, M.Sc., Universidade Federal de Viçosa**, 5th February 2024**. **Weight prediction in weaning pigs using Deep Learning techniques**. Advisor: Ilda de Fátima Ferreira Tinôco. Co-advisors: Robinson Osorio Hernandez, Jairo Alexander Osorio Saraz, Richard Stephen Gates†, Ariel Marcel Tarazona Morales†.

Estimating the weight of pigs in the weaning phase is an important process in the management of pig farms due to the adaptation conditions that the animals are exposed to. Pig farming includes several phases with very specific environmental variables such as temperature for sows and piglets before weaning. For this reason, the weaning phase is a crucial moment to guarantee an optimal weight for future phases (finisher pigs), which becomes a better income for the producers. Therefore, an automatic individual pig detection and weight prediction model was applied to detect individuals housed in groups of 10 males and 10 females under real production conditions in a naturally ventilated structure, with initial weights of 8 kg to reach around 32-40 kg. For individual detection, the Yolov7 algorithm was used together with the VGG Image Annotator, obtaining a precision of 98.3% in natural behavior (all postures and lighting conditions were included). For weight prediction, three pre-established architectures (MobileNet, ResNet50, DenseNet121) and an own created architecture (CustomNet) were compared, together with four optimizers (SGD, RMSprop, Adam and Nadam), and was selected the best architecture's performance and then, was applied optimizers to find the minimum error in weight prediction. The model with the best performance was DenseNet121 with Adam optimizer, obtaining as a result a minimum coefficient of determination R^2 of 0.96 for the analysis of males. Females and Males - Females cases obtained a R^2 of 0.98. The deep learning techniques applied, and the results obtained show the feasibility of this method and allow to optimize resources in the management of pig farms under real and challenging conditions.

Keywords: Pig’s individual detection; Yolov7; VGG Image Annotator; DenseNet121; Growth curve in pigs.

RESUMO

LOZANO CRUZ, Erika Fernanda, M.Sc., Universidade Federal de Viçosa**, fevereiro 05, 2024**. **Estimativa do peso de suínos na fase de crescimento inicial usando técnicas de *Deep Learning***. Orientadora: Ilda de Fátima Ferreira Tinôco
Co-orientadores: Robinson Osorio Hernandez, Jairo Alexander Osorio Saraz, Richard Stephen Gates†, Ariel Marcel Tarazona Morales†.

A estimativa do peso dos suínos em cada período de vida é um processo importante no gerenciamento e tomada de decisões corretas nas granjas suinícolas, devido às condições de adaptação às quais os animais estão expostos em seus ambientes de criação e que interferem diretamente em seu desempenho e no sucesso final do empreendimento. Assim, a criação de suínos inclui várias fases, com exigências ambientais muito específicas, sendo que o peso do animal na fase de desmame é crucial para garantir a obtenção de peso ideal para as fases futuras, até chegar ao suíno na terminação, resultando em maior garantia de melhor renda para os produtores. Portanto, um modelo automático de Deep Learning foi aplicado para detectar peso em indivíduos alojados em grupos de 10 machos e 10 fêmeas, em condições reais de produção e alojados em instalação naturalmente ventilada. O estudo foi realizado com suínos com pesos iniciais de 8 kg até atingir, aproximadamente, 40 kg. Para a detecção individual, o algoritmo Yolov7 foi usado junto com o VGG Image Annotator, obtendo uma precisão de 98,3% no comportamento natural (todas as posturas e condições de iluminação foram incluídas). Para a previsão de peso, foram comparadas três arquiteturas de Deep Learning pré-estabelecidas (MobileNet, ResNet50, DenseNet121) e uma arquitetura desenvolvida para esta investigação (CustomNet), juntamente com quatro otimizadores (SGD, RMSprop, Adam e Nadam). Foi selecionado o melhor desempenho da arquitetura e, em seguida, foram aplicados otimizadores para encontrar o erro mínimo na previsão de peso. O modelo com o melhor desempenho foi o DenseNet121 com o otimizador Adam, obtendo, como resultado, um coeficiente de determinação R^2 mínimo de 0,96 para a análise de machos. Os casos de fêmeas e machos obtiveram R^2 de 0,98. As técnicas de aprendizagem profunda aplicadas e os resultados obtidos mostraram a viabilidade desse método para otimizar os recursos no gerenciamento de granjas de suínos em condições reais. Além disso, as técnicas de *Deep Learning* aplicadas nesta investigação podem ser usadas para criar interfaces gráficas que analisem em tempo real o ganho de peso de cada animal.

Palavras-chave: Detecção de suínos; Yolov7; VGG Image Annotator; DenseNet121; Ganho de peso suínos.

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SUMMARY

INTRODUCTION

Pork is the most consumed meat in the world, accounting for 36%, followed by poultry (33%), beef (24%), and goat/sheep represented by 5% (USDA, 2023b). In 2021, FAO, (2022b), reported a global pork production of 122.5 million tons, up 11.5 percent from 2020, with Brazil being the largest producer after China, the European Union, and the United States. As reported by (ICA, 2023), in 2022, Colombia registered a total number of pigs of 9,658,204, of which 89.5% were animals from commercial and technical production farms and the remaining 10.5% were backyard animals. Six departments* account for 64.3% of the country's total pig population: Antioquia (26.6%), Valle del Cauca (14.7%), Meta (8.7%), Cundinamarca (7.3%) and Córdoba (7.0%), and, according to the inventory of pigs and production units reported by (ICA, 2023), Antioquia had a share of 44% of technician production units of the total technical farms existing in Colombia.

At the industrial level, 60% of the total cost of pork production is related to the cost of feeding the animals (Bhoj et al., 2022; Kyriazakis & Whittemore, 2006). This level of productivity, related to the weight gain in confined animals, is defined by (Cominotte et al., 2019) as the result obtained from the management strategies in the animal production units and to the continuous monitoring of the adequate growth of the animals. Therefore, the main challenge of the producer is to improve the feed efficiency and to monitor the weight gain in the productive phase, especially in the nursery phase, which is the stage with the greatest amount of adaptation processes of the animals to the environment (Pluske et al., 2003).

Accordingly, animal weight is an important indicator of an appropriate management, feed supply and environmental conditions that promote their growth (Apichottanakul et al., 2012; Condotta et al., 2018; G. Li et al., 2022; Minagawa & Ichikawa, 1994). In pig weighing, there are two main stages: the first corresponds to the separation of the piglets from the sow and the second corresponds to the marketing phase (Condotta et al., 2018; Pluske et al., 2003). During the weaning phase, the weight of the animals is subject to environmental adaptation, dietary changes (liquid to solid) and hierarchical relationships in the pens. By reason of piglet productivity in the first week after weaning is critical to ensure the desired weight in the final growth phase. Pluske et al., (2003) and Tokach et al., (1992), obtained a decrease in time to slaughter in piglets that had weight gain greater than 115 grams per day in the first week of weaning, compared to daily gain less than 115 grams per day.

On the other hand, weighing pigs also can be divided into two categories, direct and indirect measurements. Direct measurements use scales and require the presence of a stockman to weigh pigs. In other cases, self-weighing scales are developed to reduce human-pig contact and then avoid influencing pig behavior (H. Chen et al., 2023). However, direct methods are the most used for weighing and require at least two people and approximately three to five minutes per animal, causing stress to the animals. This activity is not feasible at the agro-industrial level due to time and labor constraints that may exist on farms (Condotta et al., 2018; Liu et al., 2020; Minagawa & Ichikawa, 1994). Therefore, it is necessary to implement technological alternatives that allow the optimization of time and resources in the determination, and that avoid or reduce the occurrence of stress to the animals.

Technological strategies based on artificial intelligence (AI) have been developed to detect characteristics that define the growth status of animals in the feedlot. Therefore, its subfields such as image processing techniques, machine learning and deep learning, have been used to detect behavioral patterns (C. Chen et al., 2021; Zhu et al., 2017), position (Nasirahmadi et al., 2019; Xu et al., 2022), weight gain (Kashiha et al., 2014; G. Li et al., 2022; Meckbach et al., 2021), management of agriculture, livestock and remote sensing (Sant'Ana et al., 2022) , among other variables (C. Chen et al., 2021). However, one of the difficulties that arise in the extraction of morphological characteristics, is to distinguish the animal and the environment, which allows to clearly obtain the information present in the image (Condotta et al., 2018; Kashiha et al., 2014).

Although many strategies based on computer vision can be implemented to optimize weighing processes, there are also variables such as lighting conditions (Kongsro, 2014) that can affect image processing when extracting morphological features or applying thresholding transformations to binary images (Solomon & Breckon, 2011), as occurred in their study.

The implementation of deep learning techniques in this research required the use of artificial neural networks (ANN). In accordance with (Topuz, 2010), the artificial neural networks are computational (ANN) models, which simulate the function biological networks, composed of neurons and has been widely used to process prediction. The system has three layers of neurons: input layer, a hidden layer, and an output layer. The input layer is all the input factors, then this information is processed through a hidden layer, and finally the following output vector is calculated in the output layer. Therefore, ANN has a high efficiency through nonlinear mapping when applied to feature recognition with noisy and incomplete data (Apichottanakul et al., 2012) and can reduce the stress in the weighing process by being a noninvasive method (Benjamin & Yik, 2019; Y. Wang et al., 2008).

One of the various types of ANN, is Convolutional Neural Network (CNN), which is applied in several tasks such as detection, classification, recognition, and tracing (Bezen et al., 2020) and the main advantage is the ability to find complex relationships in data. This advantage is due to ability of the model to learn from observed data requiring little or no prior knowledge of the task to be performed (Ye et al., 1998).

Therefore, to address issues in image processing caused by varying lighting conditions and the application of morphological transformations, deep learning techniques were employed in this research. These techniques included image augmentation, boundary processes, training, and neural network validation, using frames from videos regardless of ambient light or camera lens perspective. In this study, 1-minute videos of 20 animals with an initial weight of 8 kg, separated into two cages, 10 males and 10 females, were used. Videos were recorded from 6 am to 6 pm for 6 weeks until the animals reached a suitable weight of approximately 40 kg. This procedure was repeated 4 times over 9 months leaving 30 days between trials.

The objective of this work was to develop a system for predicting the weight of pigs in the weaning phase using deep learning techniques under challenging conditions. To estimate the weight of the animals, it was proposed to develop an automatic system for the individual detection of male and female pigs and then to correlate the actual weight of each animal with its morphological measurements learned by convolutional neural network model and the use of the YOLOv7 algorithm.

The results of this research are presented in three chapters, as follows:

CHAPTER 1

WEIGHT MEASUREMENT STRATEGIES IN SWINE PRODUCTIONS: A REVIEW

CHAPTER 2

INDIVIDUAL PIGLET DETECTION IN WEANING STAGE USING DEEP LEARNING TECHNIQUES

CHAPTER 3

PIG WEIGHT PREDICTION OF MALES AND FEMALES IN WEANING STAGE

OVERALL CONCLUSION

CHAPTER 1

WEIGHT MEASUREMENT STRATEGIES IN SWINE PRODUCTIONS: A REVIEW

Ilda de Fátima Ferreira Tinôco, Robinson Osorio Hernandez, Veronica Gonzalez Cadavid, Jairo Alexander Osorio Saraz.

1. WORLDWIDE AND COLOMBIAN PORK PRODUCTION

The global pork production for 2024 was revised down 1% from October 2023, representing a total of 114.15 million tons around the world, with China (55.4 million tons), European Union (22.3 million tons), United States (12.3 million tons) and Brazil (4.3 million tons) as the principal producers and consumers and are projected nearly 60% of global meat output by 2029 (OECD/FAO, 2020; USDA, 2024). Even though pork production decreased 1%, the production and consumption reached the highest worldwide rates, constituting 36% of global meat intake (World Population Review, 2023), compared with poultry and beef trades (USDA, 2024), as shown in Table 1.

In total growth meat consumption pigmeat is projected as the second largest contributor for reaching 93 Mega tons (hereafter Mt) of retail weight equivalent (hereafter r.w.e) and is predicted to increase 0.6% in global production by reaching about 129 Mt, by 2032 (OECD/FAO, 2023). Pig and poultry meat are the biggest sectors, constituting 58% and 28% of total Chinese meat production, respectively. Pigmeat production is expected to recover in Asian African Swine Fever-affected countries, growing by 19% in China, the largest producing country.

Latin American countries provide 16% of global livestock production and are expected to rise the consumption by 2.9 kg per capita to almost 53 kg/person/year by 2032, derived from poultry meat and pigmeat (OECD/FAO, 2023). And Latin American pork production is expected to reach 8.6 million tons (Mt), an increase of 3.6% in 2024 compared to expected production (8.3 Mt) in 2023 (Pig333, 2023b).

Table 1. World meat and poultry market (production and consumption) for 2024 forecast. Adapted from:(USDA, 2024)

Worldwide statistics	Pork (million tons)	Poultry (million tons)	Beef (million tons)
Production	114.2	103.5	59.2
Consumption	113.8	100.8	57.7

At the country level, per capita consumption varies widely among meat types. In Colombia the per capita pork consumption was 13 kg/person/year in 2022 (Asociación Pork Colombia, 2023) and among top 5 countries increase and decrease in per capita consumption, Colombia is predicted to increase by around 2kg r.w.e for 2029 compared to 2017-2019 years (OECD/FAO, 2020).

Regarding pork Colombia's production (Pig333, 2023b) reported 526.000 tons Colombia production by 2022 (Pig333, 2023b) representing 0.5% of global production for the same year (USDA, 2023a).

2. PIG PRODUCTION CONTEXT IN COLOMBIA

Pig production in Colombia is divided into semi-automated, automated, or traditional infrastructure and presents one of the central problems which is profitability due to production costs. It is clear that, among other factor, pig breeding primarily aims to improve lean meat production and carcass yield (S.-H. Lee et al., 2023) and since Colombia has one of the highest production costs in Latin America for standing pigs due to feeding costs, representing 73.25 % of the total production costs, followed by labor costs (6.04 %), and finally, installation costs (3.56 %) (Trujillo-Díaz et al., 2021).

The first level of industrial transformation in Colombia is associated with the livestock or pig breeding stage, followed by the first level of industrial transformation. At the agro-industrial level, the productive stage with the highest participation in input consumption was rearing with 65.10%, followed by pre-fattening with 18.30% and females with 13.34%, according to the National Administrative Department of Statistics (hereafter DANE) (DANE, 2022). Therefore, pigmeat and poultry prices show a strong link to feed costs as their production uses more grain and protein meal-based feed (OECD/FAO, 2023).

The production of the industrial phase of pig farming at the first level of processing went from 5.8 billion pesos in 2019 to 7.8 billion pesos in 2021. The by-product that obtained the highest representation was meat in carcasses, which increased from 5.2 billion pesos in 2019 to 7 billion pesos in 2021, representing 89.3% of total production (DANE, 2022).

In Colombia, statistics are generated through satellite accounts that correspond to branches of the System of National Accounts. These accounts provide an economic perspective on the agroindustry in the country, combining analyses of productivity, agriculture, and industry (Pig333, 2023a).

The swine agro-industry's total output in Colombia is the combination of the livestock and industrial phases at the first level of transformation. By 2021, the industrial phase contributed 57.37% of income in the pork production chain in Colombia and the livestock phase contributed 42.63%. Although the industrial phase contributed more income, this phase is conditioned to the level of production and breeding of pigs in the livestock phase. Thus, the production value of the swine agro-industry in 2021 was 13.63 billion, 26.7% higher than in 2020 (ASOCIACIÓN PORKCOLOMBIA, 2022).

In the first semester of 2022, Colombia recorded a 7.4% growth in pork production, marketed at record prices due to the lower consumer price fluctuation (-2.02%) compared to other meats. As for the pork profit, the first semester of 2022 has a growth of 7.21% compared to the same semester of 2021, which corresponds to 176,892 additional heads (ASOCIACIÓN PORKCOLOMBIA, 2022).

However, (ICA, 2023) reported statistics on automated production in all departments of the country and the number of farms with Backyard, Family production units, Industrial production, and Automated facilities. According to Figure 1, the first five departments with the highest number of pig farms are Antioquia, Valle del Cauca, Meta, Cundinamarca, and Córdoba.

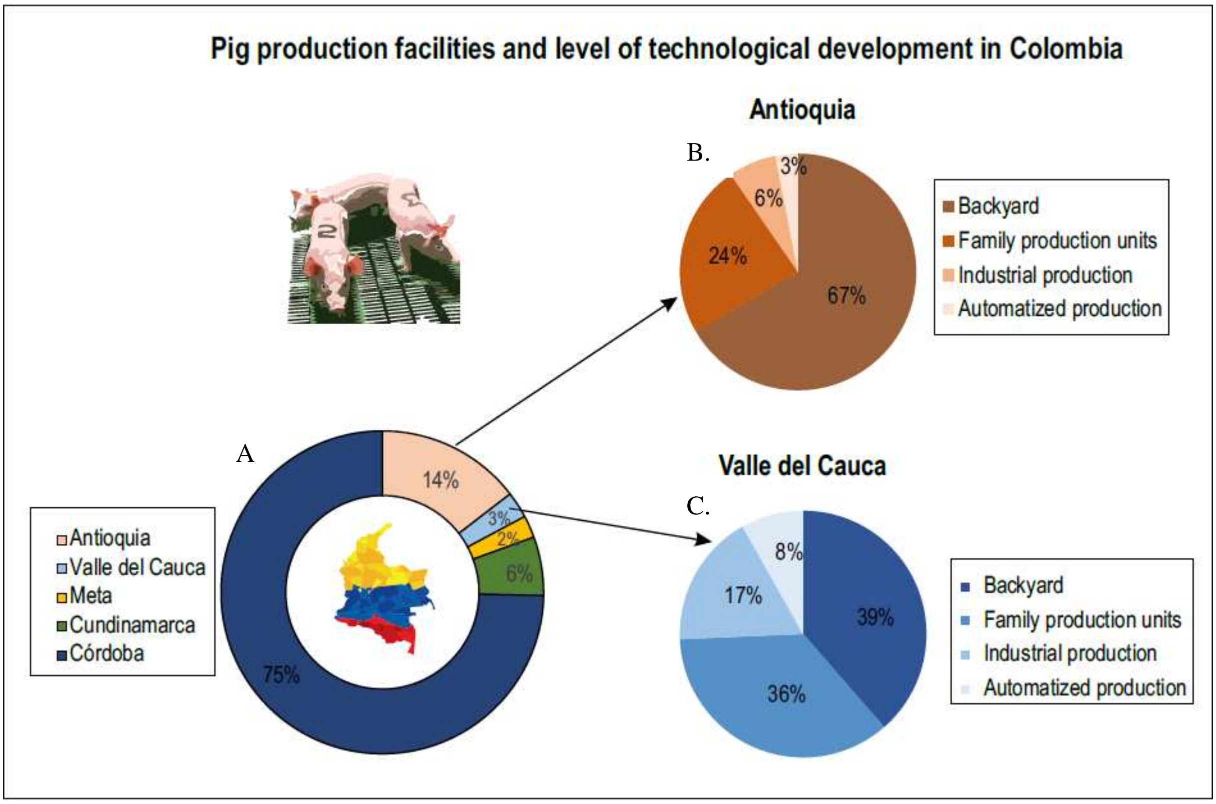

Figure 1. Top 5 pork producers Departments in Colombia and level of technological development of the two first Departments with the highest technological development in Colombia. A. Total pig production facilities in top 5 Departments in Colombia. B. Level of technological development in Antioquia. C. Level of technological development in Valle del Cauca. The total number of facilities analyzed included only the statistics of those 5 Departments. Source: Data adapted from (ICA, 2023).

Figure 1A shows that 14% of the farms that have pig production are located in the Department of Antioquia, and of these facilities, only 3% are automated. On the other hand, figure 1C shows the Department of Valle del Cauca, which, although it does not have most pig farms, of the 3% that are used for raising pigs, 8% of those lands are automated. In other words, only 0.86% of the total number of farms analyzed in the five departments have automated production.

In light of these factors, Colombia's pork production is hindered by a lack of technological development facilities, resulting in process delays, decreased efficiency, and profitability. This will ultimately lead to improved efficiency and profitability. Strengthening technological development on farms is crucial to reducing costs during the resource-intensive raising and pre-fattening phases (DANE, 2022).

Therefore, using tools such as artificial intelligence in the early stages of production can improve resource efficiency. Ensuring knowledge of the growth of each animal guarantees profitability for the producer and optimal quality for the consumer or slaughterhouse.

3. PORK PRODUCTION CONDITIONS IN COLOMBIA

For the swine census in Colombia, the pork production conditions are presented by type of farm: backyard, family commercial, industrial commercial and technical production, and by swine category: breeding females, replacement females, breeding males, and a category that groups breeding and fattening pigs.

There are a total of 192,675 farms in the country, categorized as follows: 79% (152,069) are backyard farms, 19% (35,797) are commercial family farms, 2% (4,025) are commercial industrial pig farms, and the remaining 0.4% (784) are technical production farms. The total number of registered animals is 10,639,149, with 62% being animals on technical production farms, 17% being pigs on commercial industrial farms, 12% being commercial family pigs, and 9% being backyard animals (ICA, 2023).

4. ARTIFICIAL INTELLIGENCE IN PIG WEIGHT MEASUREMENT

The weight of animals in pork farms is determined by various factors involved in the production chain. Live weight measurement and prediction are crucial processes for decision-making during the shipping stage. Knowledge of the weight achieved by pigs enables traceability of their growth curve and facilitates corrective actions when weight gain is affected. (W. Lee et al., 2019; Taylor et al., 2022). Therefore, it is crucial to establish tools for determining the weight of animals in real production conditions to optimize resources and keep in balance a non-invasive method and a higher economic efficiency.

Several methods exist for measuring and predicting animal weight, ranging from manual measurement to artificial intelligence predictions. More recently, machine learning algorithms including differential recurrent neural networks (Demmers et al., 2018) and digital image processing are the most widely used vision-based weight prediction methods (Paudel et al., 2023). Some authors such as (Bakoev et al., 2020; Paudel et al., 2023; Taylor et al., 2022) have contributed to this field.

However, in order to predict a pig's weight with high accuracy, prior and high-quality data must be recorded. This data collection process remains a major barrier to progression of research in precision agriculture for pig farming (Taylor et al., 2022). In this way, several studies have been carried out in research conditions, which makes it difficult to reflect the real conditions of production and the needs of the farmers. This is why it is important to have a general notion of the situation in which a certain weight prediction method can be applied. The objective of this chapter was to establish a general notion and state-of-the art of the most recent studies that have been published related to swine weight prediction, the stages, production conditions evaluated.

An important indicator to be considered is the accuracy of estimation. Authors such as (W. Lee et al., 2019; Ruchay et al., 2022) found that through the evaluation in machine learning processes, the accuracy of estimation for growth performance is heavily dependent on the pre-process of growth data. (W. Lee et al., 2019) confirmed that the accuracy can be improved by 28% using machine learning techniques and (Ruchay et al., 2022) utilized a dataset including 340 pigs and propose a comparative analysis of various machine learning methods using outlier detection, normalization, hyperparameter optimization, and stack generalization. The Stacking Regressor model was found to provide the best results with an MAE of 4.33 and a MAPE of 4.296% on the testing dataset.

In other hand, the main research tasks in animal husbandry are the discovery of the biological mechanisms influencing animal productivity and finding efficient ways of increasing it (Bakoev et al., 2020).Thus, growth performance can be influenced by several factors, such as feed intake (W. Lee et al., 2019), daily of body weight, required growth period for growing/finishing phase (Taylor et al., 2022), climate, initial body weight, number of pigs and stocking density in commercial farms.

Morphometrics measurements are also important to predict live weight. For instance, (Ruchay et al., 2022) found that chest girth represents over 20% of importance for predicting the pig live weight using StackingRegressor algorithm. In the study developed by (Ositanwosu et al., 2023), they constructed a 3D model of a pig and developed MLP f Multilayer Perceptron Neural Network NN models, which are a feed-forward ANN, incorporated the Adam Optimizer and ReLU activation functions and this prediction approach was applied after body parameters such as length, height, width etc, obtained from light depth-cameras (Microsof Kinect™ v2).

Other approaches include mixing weight prediction and tracking on pigs on an individual-level using RFID tagging (Radio-frequency Identification) to estimate growth trajectories and identifying potential diseases or behavioral situations in an industrial level (Taylor et al., 2023).

In other hand, shipping weight of fattening hogs has been studied also in pork production systems and a timely and accurate estimation of body weight in finishing pigs is critical in determining profits by allowing pork producers to make informed marketing decisions on group-housed pigs while reducing labor and feed costs (Y. He et al., 2021). An optimal system for determining the shipping schedule for pigs using a predictive using a model machine learning based on big data was proposed by (Jang et al., 2023). The model predicts the minimum weight required for shipping by analyzing weight gain patterns of pigs that form abdominal fat and monitoring the weight changes in the selected pig.

Taylor, C., Guy, J. & Bacardit, J. (2022) developed machine learning models to predict the length of time taken for growing pigs to reach target finished weight based on data sources that could potentially be captured in commercial conditions. However, they obtained a limitation with maximum time registered when weight gaining prediction was over 65 days. This time in growing process also can be related with variables associated to the usefulness of feeding behavior data in predicting the body weight of pigs at the finishing stage as researched by Yu, H., Lee, K., & Morota, G. (2021).

Other studies utilized Deep learning techniques for weight estimating have been developed, such real-time and mesh reconstruction from point clouds using Deep Neural Network (Ositanwosu et al., 2023), 3D deep learning architecture (PointNet) to predict weight from point clouds (Paudel et al., 2023). Furthermore, weight determination based on convolutional neural networks was applied solely on the depth images of pigs, without further feature extraction and achieving a high coefficient of determination $R^2 = 0.97$ (Meckbach et al., 2021). It is important to mention that each case study has a different approach depending on all initial conditions. For example, (Meckbach et al., 2021) mentions that providing solely the images and the related weight to the ConvNets is sufficient to reach an accurate weight prediction, but they utilized pigs from 20 and 133 kg in a single animal scale what facilitates the individual detection.

Tan, Z., Liu, J., Xiao, D., Liu, Y., & Huang, Y. (2023) addressed their study to tackle variable lighting and the complexities of measuring pigs in constant motion developing an innovative algorithm based on Deep Vision (MPWEADV). The weight of moving pigs was estimated using RGB and depth images. However, analyzing each individual in constant motion was limited when encountering images with severe occlusion.

Another relevant approach is weight prediction collecting RGB- D videos as developed by He, Y., Tiezzi, F., Howard, J., & Maltecca, C. (2021). Nevertheless, this method has a specific challenge of choosing the best frames to be incorporated in the model as such the authors established. They obtained a lower coefficient of determination (R^2 = 0.72) when pigs were not restrained (R^2 = 0.98) compared to the restrained scenario, in this case another feature is taking importance, the animal positions.

Vision Analysis and Prediction is another approach which weight prediction could be carried out. Segmentation processes and statistical analysis was presented by Tu, G. J., & Jørgensen, E. (2023) reaching an accuracy of 97.76%.

On the other hand, smartphones have been utilized for pig body measurements and prediction of body weight as (Thapar et al., 2023) mentioned. They developed a novel, portable and user-friendly method for hands-off measurement of body dimensions and prediction of body weight of the Ghoongroo breed of pigs (aged 30 to 190 days) using a smartphone object measurement app- On 3D CameraMeasure and regression analyses to predict body weight. Nonetheless, the authors obtained images from each pig and very specific animal positions.

In addition to all the above, many variables can be analyzed to weight prediction, including production stage, age of animals, feed, environmental conditions, etc. For instance, (Kaiser et al., 2023) focused their study on nursery pigs to determine the height in nursery pigs (5 - 40 kg) by knowing the body weight as part of the pre-transport management of the pigs in European pig production. Moreover, studies as aimed by (Preethi et al., 2023) which studied nursery pigs also. They identified the best estimator boy weight based on various linear morphometric measures using artificial neural network (ANN) and non-linear regression models at three life stages (4^{th}, 6^{th} and 8^{th} week) and obtained a best performance in 8^{th} week aged pigs with a R^2 = 0.913, so the performance in 4^{th} was lowest.

This shows that determining the weight of animals during early stages of production, such as nursery and weaning, can be more challenging than other stages due to their size and behavior. This highlights a lack of studies in literature that focus on early stages of pig production. Identifying growth during these stages can aid in making preventive decisions regarding any abnormalities or behaviors exhibited by the piglets. This could lead to greater efficiency in the production chain and provide farmers with more information on pig breeding performance from weaning, reducing future problems that may occur in the final marketing phase. Table 2 shows the multiple factors studied by several authors under different production conditions using artificial intelligence methods, as well as the lack of research presented in the initial stages of pig production.

Table 2. Weight prediction factors studied by several authors under different production conditions using artificial intelligence methods.

Reference	Data acquired	Growth stage	Pigs weight range	Study conditions	Estimation Error / Coefficient of determination/Pearson's correlation coefficient/Accuracy	Models/Algorithms	Weight Estimation Techniques	Categorical variables
(Taylor et al., 2022)	Food consumption	Grower finisher	50 - 90kg	Commercial	**R** = 0.962	Cross-validation, ReLU, LSTM neural network/Random forrest/Adaboost/LASSSO	Deep Learning	Feed intake
(Lee et al., 2019)	Images	Growing pigs	up to 105kg	Commercial	**Acc=** 79.64% Random Forest	Logistic regression /Random Forest /SVM	Machine Learning	THI/Feed intake
(Bakoev et al., 2020)	Images	-	-	-	**Acc=** 88% con RF model	XGboost algorithm /Random Forest/SVM/Naivebayes/ANN	Machine Learning	Average daily weight
(Ruchay et al., 2022)	Images	Finishing	86 - 113kg	-	**R^2=**0.369, **RMSE=**5.226, **MAE**=4.319, **MAPE**=4.281	Random Forest/adaBoostregressor/CatBoostRegressor/(LGBMRegressor)	Machine Learning	-
(Taylor et al., 2023)	Images	-	50 - 90kg	Commercial	**RMSE**= 1.52kg	Random Forest/Gradient Boosting/Multilayer Perceptron/SVM	Machine Learning	-
(Jang et al., 2023)	Images	Fattening	-	Individual	**Acc**= 0.94 XGBoost and Lightgbm Models	Gradient Boosting Classifier/XGBoost/LightGBM/CatBoost/KNN	Machine Learning	Object recognition, Weight measurement, Feed amount measurement
(He et al., 2021)	Images	Finishing	-	-	**Acc**=0.74, RMSE= 14.3jkg	LASSO regression / Random Forest / Long Short-term Memory network	Machine Learning	Feeding behavior, Feed intake, and body weight information
(Nguyen et al., 2023)	3D point clouds	Finishing	25 -70kg	Individual	**MAE**= 4.06 kg, **RMSE**= 4.94 kg	SVR, MLP and AdaBoost regression		-
(Kwon et al., 2023)	Manual /Automatic	Farrowing sows	168 -313 kg	Individual	**MAE**= 4.88kg, **MAPE**= 2.11%	Adam optimizer / Deep Neural Network	Deep Learning	-
(Ositanwosu et al., 2023)	Images / Manual	3 Freely walking pigs	-	Individual	**RMSE**= 5.5	Multilayer Perceptron Neural Networks /Light Depth-Cameras (Microsof Kinect™ v2) / Adam Optimizer		-
(Paudel et al., 2023)	Images	Finishing	20 -120 kg	Individual	**R^2**=0.94, **RMSE**= 6.79	PointNet/3D Deep Learning Architecture /3D Convolutional Neural Network	Deep Learning	Volume vs Weight correlation
(Chen et al., 2023)	Manual	Finisher / Boars and Sows	>40 kg	Individual	**R^2**= 0.63, **MAE**=1.85, **RMSE**= 5.74, **MAPE**= 1.68.	Radial Basis Function Neural Network	Machine Learning	Body measurements (lenght, heart girth, body width)

Reference	Data acquired	Growth stage	Pigs weight range	Study conditions	Estimation Error / Coefficient of determination/Pearson's correlation coefficient/Accuracy	Models/Algorithms	Weight Estimation Techniques	Categorical variables
(Meckbach et al., 2021)	Videos	Growing finishing	20 -133kg	Individual	**R^2**=0.97, **MAE**= 3.40 kg	CNN - Pre-trained ConvNet EfficientNet-B0 c	Deep Learning	-
(Cang et al., 2019)	Top view depth images	Farrowing sows	120 -200kg	Individual	**MAE**= 0.644kg	Deep Neural Network - Faster R - CNN / Adam Optimizer	Deep Learning	Pig recognition, Location, Weight estimate
(Tan et al., 2023)	Deep vision	Finishing	60 -150kg	Individual	**R^2**= 0.901, **MAE**= 2.856, **MAPE**= 2.383%, **RMSE**= 4.082kg	ConvNetXtV2 Network	Machine Learning	-
(Yu et al., 2021)	RGB images	Post weaning	7.6 - 8.7kg	Individual	**R^2= 0.72**	Image Processing / Linear Mixed Effects Model (LMM)	Artificial Vision	-
(Tu & Jørgensen, 2023)	Videos	Growing pigs	20 -105kg	Group	**Acc**= 97.76%	Images Segmentation /Best Linear Unbiased Prediction (BLUP)	Artificial Vision	Body measurements (lenght, perimeter, area)
(Thapar et al., 2023)	Images	Growing - finishing	30 -190 days	Individual	**R^2**= 0.97	App 3D CameraMeasure	Others	Body measurements
(Kaiser et al., 2023) *	Estimated Height from weights	Weaning	5 - 40kg	Individual	**R^2**= 0.95, **RMSE**= 1.62	Polynomial Regressions/Power Function		Height and Weight
(Preethi et al., 2023) *	Manual	**Pre - weaning** (4th week) **Weaning** (6th week) **Post weaning** (8 week)	-	-	**R^2**= 0.8697, **MSE** = 0.4419 - **4th week** **R^2** = 0.8528, **MSE** = 0.8719 - **6th week** **R^2** = 0.9139, MSE = 1.2713 - **8th week**	ANN infrastructure for trait screening / Nonlinear regressions/Linear regression /Bayesian Regularization Backpropagation training function (TRAINBR)		Morphometric traits (linear body measurements: Body length, heart girth, head length, etc.)

Source: Adapted from cited authors.

*Authors studied initial stages of pig production to predict live weight.

5. MATERIAL AND METHODS

5.1 Identification and Literature search

The search syntax was performed using the following combination of terms (“pigs*” OR “swine”) AND (“weight*”) AND (“prediction” OR “estimation”) AND (“artificial”) AND (“intelligence”) using Scopus and Web of Science databases from inception to January 2023 to locate the most relevant and recent studies.

5.2 Screening using Machine Learning

The search process included studies that: (1) investigated weight prediction in different pig stages productions; (2) were published in English language; (3) were published articles; (4) were published in the last five years.

Studies were excluded if: (1) were reviews or meta-analysis; (2) did not include artificial intelligence methods for weight prediction; (3) were duplicated articles from both databases.

It was founded in 100 articles in the first step of filtering from databases, after excluding 50 for the next step of manual screening using Revtools library from R Studio. After this first screening, was implemented an automatic screening using machine learning methods (ASReview LAB and Python). This step is crucial because manual screening cannot eliminate all duplicate items, as symbols in study titles may prevent their recognition and exclusion.

5.3 Eligibility

After the two screening processes, all information needed from articles, such as title, DOI, abstract, authors, etc. It was compiled in a table in Excel to future identification of variables assessed in each study. In this stage, it was finalized the inclusion and exclusion criteria that were not defined in the previous steps. This is related to reviews or meta-analysis documents that may have been applicable in previous steps but were not considered for this study. A total of 20 articles met the inclusion/exclusion criteria. (Table 1 and Figure 2). The flowchart of method established is presented in Figure 2 using an R package and Shiny app named PRISMA (Haddaway et al., 2022).

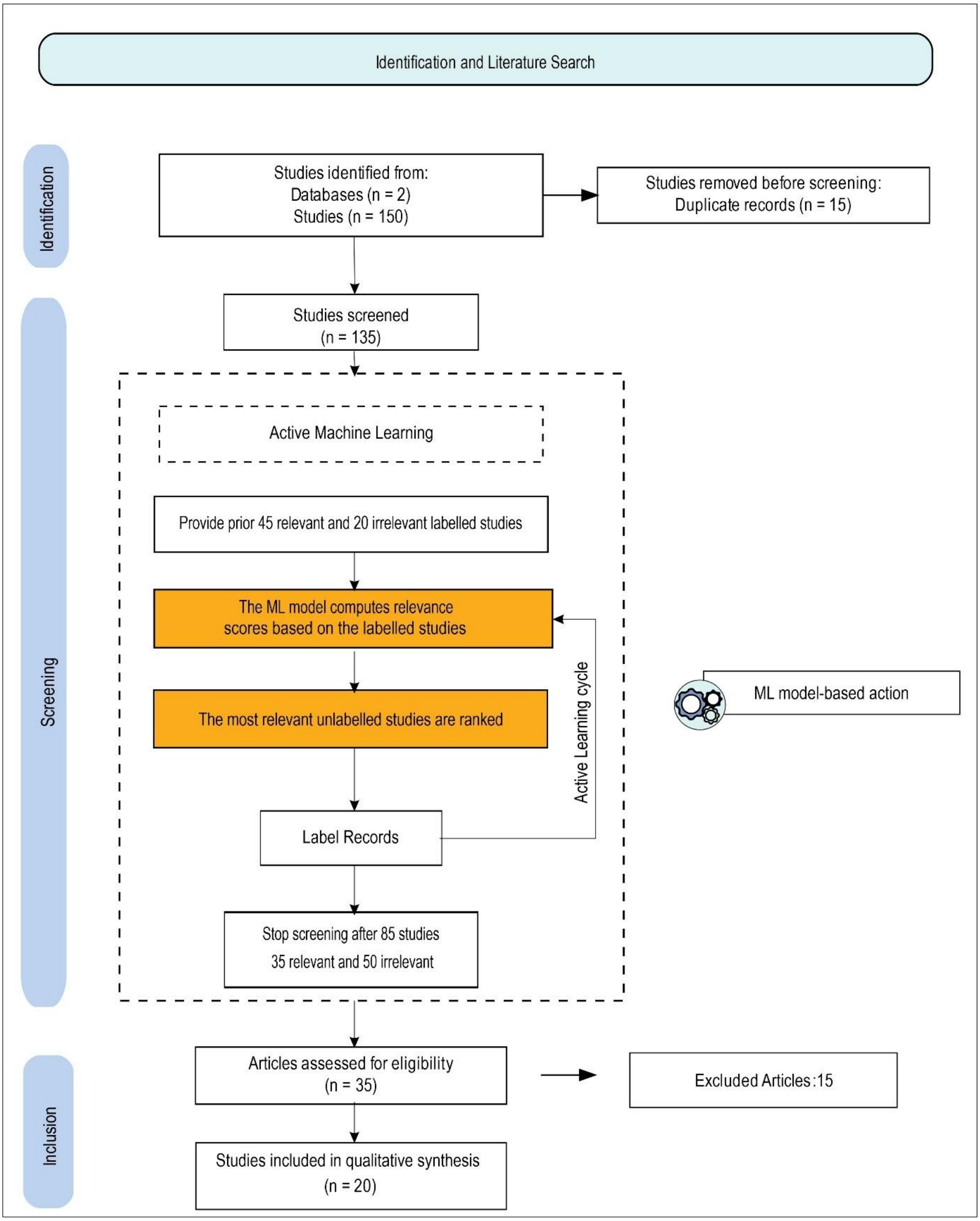

Figure 2. PRISMA Flowchart of the search process.

6. RESULTS

After identification, screening, and eligibility process, 20 articles were selected as state-of-art in artificial intelligence techniques utilized in pig weight prediction in the last five years. As Table 2 shows, a qualitative analysis was developed using several categorical variables to exclude or include research.

In this sense, a qualitative synthesis was developed with the three principal variables listed in Table 2, which were Weight estimation techniques, Growth stage and Studies conditions.

Figure 3 shows all the articles classified by those three factors demonstrating the lack of study of swine productions in early stages such as pre-weaning and weaning when animals are housed in groups in a real condition. Most of the studies founded were focused on growing and finishing stage and individual conditions.

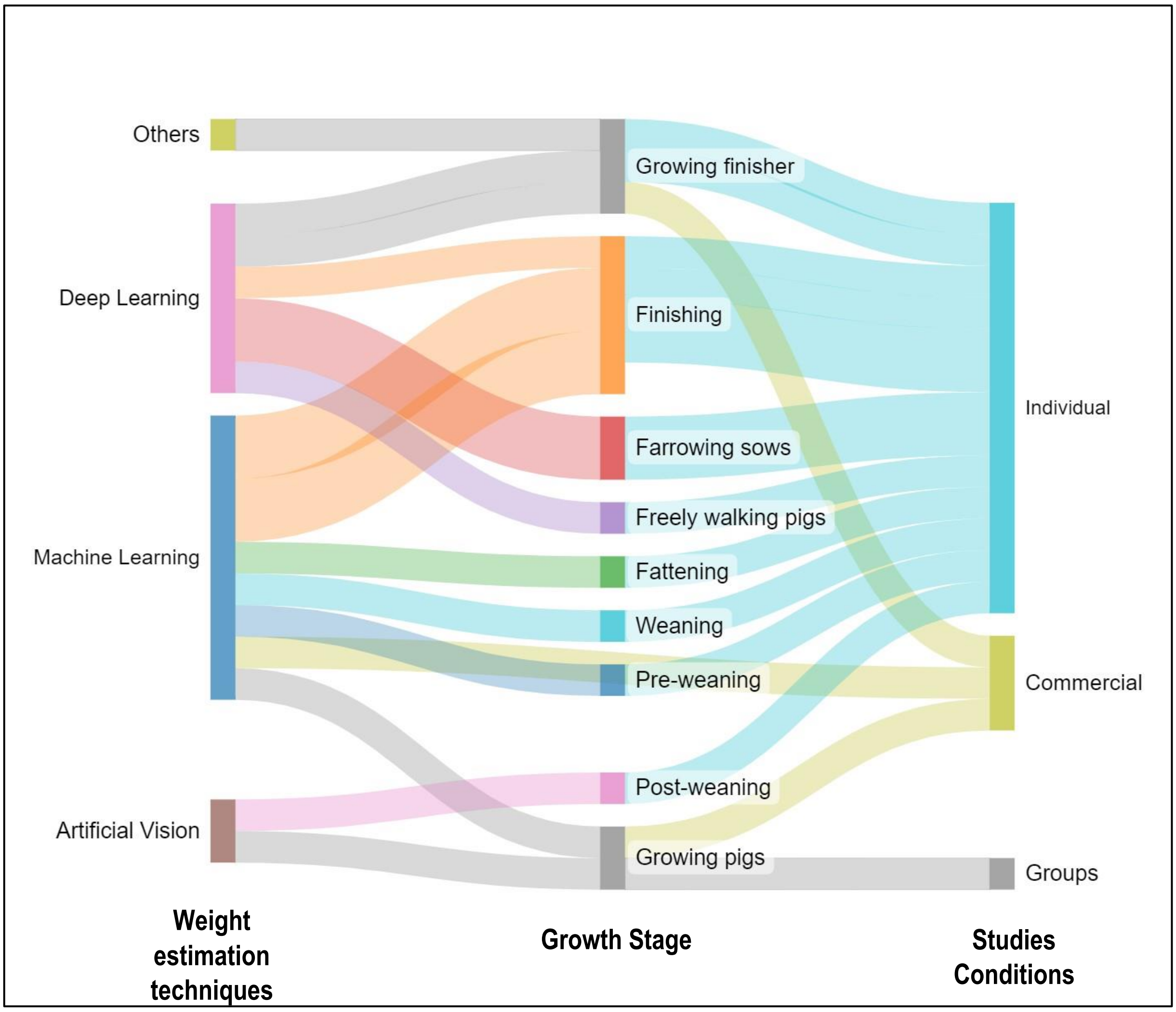

Figure 3. Qualitative synthesis of artificial intelligence techniques utilized in pig weight predictions.

In regard to weight estimation techniques, it was demonstrated that Deep Learning techniques were less utilized than Machine learning, and none of all cases applied in Deep Learning were focused on weaning pigs, considering weaning as the stage where piglets are separated from sow and the diet changed to a solid - based diet.

7. CONCLUSIONS

Based on the results obtained, recent studies have primarily focused on the final stages of pig production, specifically growing and fattening. During these stages, it is important to ensure that the animals are fully adapted to their environmental and feeding conditions. Analyzing images or videos of animals in these stages is easier due to the ease of detecting each individual and measuring their morphometric characteristics through artificial intelligence techniques.

The literature commonly predicts weight by analyzing individuals in controlled measurement conditions, such as manual scales, while taking images or videos. Even studies that analyzed commercial conditions included individual animal selection during data collection.

Additionally, Deep Learning techniques have not been frequently applied in early stages of pig production, such as weaning or nursing, indicating a lack of research in this area.

Despite the information provided, it is insufficient to identify the adaptation process of piglets after the nursing stage, which is reflected in their growth and weight gain. This stage is crucial in achieving the optimum weight at the end of the production chain. Therefore, it would be beneficial to include additional studies that examine the variables of adaptation from liquid to solid diets in real production conditions. The study delineates the process of tracking piglet growth during adaptation and its impact on weight throughout the productive chain.

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CHAPTER 2

INDIVIDUAL PIGLET DETECTION IN WEANING STAGE USING DEEP LEARNING TECHNIQUES

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ABSTRACT: Pig farms management is involved in multiple factors such as environmental conditions, animal behavior, weight gaining and others. In all those scenarios, it is fundamental to detect each individual and its development as it grows to reach the shipment phase. Therefore, the objective of this chapter was to apply an automatic individual pig detection algorithm using Deep Learning Techniques, in frames taken from videos recorded during the weaning phase in real production conditions of small and medium producers in tropical conditions in Colombia. The weaning phase was selected because individual detection in each cage is more difficult due to environmental adaptations that piglets undergo after nursing. Piglets tend to cluster together during this phase, making image processing more challenging compared to the fattening phase, where animals are more isolated. The You Only Look Once (YOLOv7) algorithm and VGG Image Annotator were used to detect individuals in two pens separated by gender. All animal postures, lighting conditions were considered. The Precision, Recall and mAP metrics were used to assess the model performance with different confidence values. A precision of 98.3% in a threshold of 0.9 was reached, Recall of 98.5% in a threshold of 0.85. Data augmentation techniques were important to increase the dataset and to have a more realistic model for individuals' detection. The method used allowed us to identify all the complete pigs' bodies under different posture and lighting situations.

Keywords: Object detection, Yolov7, VGG Image Annotator, pigs' individual detection

1. INTRODUCTION

Object detection is the way to localize objects by automated methods in an image or video (Liu et al., 2020) and is a crucial middle level task in computer vision which facilitates high level tasks such as action recognition and behavioral analysis (Zhang et al., 2019). There are several methods for object detection, but the most effective algorithms include deep learning (J. Huang et al., 2017; Shen et al., 2021). Compared to traditional Machine Learning methods, Deep Learning is a subfield of machine learning that automatically extracts features using artificial neural networks (ANNs) as the backbone of their algorithms.

By contrast, machine learning requires human intervention to extract image features (Z. Yu et al., 2022) to train models and can work well on a wide range of important problems. However, they present failures in problems as recognizing speech or recognizing objects (Goodfellow et al., 2016). Therefore, Deep Learning was motivated by the disadvantages mentioned and their insufficiency in learning in high-dimensional spaces. In case of Deep Learning, object detection is characterized by two types of detection: one-stage detection as YOLO (Redmon et al., 2016) and two-stage detection as Faster R-CNN (Ren et al., 2015).

Depending on the parameters to be evaluated and the cameras used, the methods for extracting physical characteristics through image analysis can vary. For instance, Kongsro, (2014) used a manual selection criterion: out of 50 images taken of each animal, the single best image was selected in which the entire body of the pig appeared in eating positions to ensure less movement and the most uniformity. However, this method is extremely vulnerable to the influence of the posture of live pigs, because it requires higher accuracy for the captured images and the pigs need to be in a fixed position (H. Chen et al., 2023).

The performance in machine learning models improves in the presence of more data. To increase the data bank, it is necessary to apply geometric transformations to the images, to increase the quantity, this process is known as “data augmentation” (Srinivas et al., 2016). According to (Biase et al., 2022; Chatfield et al., 2014) both the collection of individual data and the use of the geometric transformations data such as, random cropping, small rotations, image flipping or RGB jittering to generate more examples of the class; are a valuable source of information for decision making obtaining an improvement of up to 3% in the performance of the model. Therefore, object recognition is susceptible to dataset augmentation because transformations do not change the class, but it increases the number of images with many geometric operations (Goodfellow et al., 2016).

On the other hand, there are methods such as that proposed by (Zhu et al., 2017), where a sequence was implemented to extract individual features of pigs, in cages with groups of seven individuals, on videos recorded by 2D cameras. However, this analysis represents the detection of each individual at a distance from each other. Therefore, although the information present in a video is more extensive compared to a series of images, it is challenging to process the video in terms of information storage and analysis of the frames with the most relevant information about the distance state of the pigs in the cages. To detect the position of the pigs, there are methods (Cominotte et al., 2020; B. Li et al., 2019; S. Tu et al., 2021) that identify the body dimensions of the animals, through methods such as fitting to geometric figures, or classifiers such as Support Vector Machine (SVM). The SVM classifier has the advantage of requiring less data to train the model, compared to other neural networks (Nasirahmadi et al., 2019). However, classifiers such as SVM have not yet been implemented in animal weight prediction, so there is a need to develop a neural network to articulate pig size variables, with their corresponding weights.

(Zhang et al., 2019) proposed a 2D video camera-based multiple pig detection and tracking method. They coupled a CNN-based detector and a correlation filter-based tracker via a novel hierarchical data association algorithm tackling image processing problems such as lighting, occlusion, shadows, and shape deformation.

Part of machine learning processes is the image segmentation technique which is one of the more important initial phases to carry out artificial vision techniques. However, this stage is sensitive to variables such as lighting and controllable environments differentiating objects with background (Bhoj et al., 2022). Hence, (Kashiha et al., 2014) found better performance in their algorithms only for white animals on a dark floor, which are not suitable for implementation in commercial farms with different backgrounds, illumination conditions, and animal coat colors.

On the other hand, authors as (Liu et al., 2020), worked with videos to detect cow structure by spatial positions of the joints and body localizations (key points). These body locations and joints can analyze body structure, and estimate, body, and weight, describe a spatial location of the cow, the body contour, the positions of the major joints, and the trajectories of their movement. However, this method needed several cameras from different views to detect the animal's shape through joint points and it is evident that posture is a key factor in precision on variables mentioned before.

In this way, complexity and effectiveness of models are generally influenced by choices made in image collection and segmentation (van der Stuyft et al., 1991), which can be used to detect potential production concerns and implement management strategies (Leonard et al., 2019) .

To address these drawbacks, the objective of this chapter was to apply an automatic individual pig detection algorithm using Deep Learning Techniques (The You Only Look Once (YOLOv7) algorithm), considering the real production conditions of small and medium producers in Colombia, analyzing piglets from the weaning phase. Several studies have been conducted on individual pig detection. However, this study sets a benchmark for identifying animals using Deep Learning techniques in early stages of growth under real production conditions. It is worth noting that the video-based detection process enables daily monitoring of animal activity and traceability of animals that are not developing optimally.

In this way, video processing in the weaning phase becomes more challenging because the animals are in a transitional stage from the nursing phase with a liquid diet fed by the sow, to a solid diet and are also experiencing new environmental conditions. For this reason, the identification of each animal in two cages during these adaptations, without controlling the scenarios to record the videos, such as posture, quantity of animals, or lighting conditions, was the mean purpose of this research.

On the other hand, it is crucial to achieve high precision in animal detection. This process enables other applications, such as weight prediction, identification of behavioral patterns, or decision-making for facility adaptations to improve efficiency and productivity.

2. MATERIAL AND METHODS

2.1 Location and swine production features

The research was developed at the farm of the National University of Colombia, at the Department of Agricultural Engineering – Animal Science, Medellin headquarters at 2154 m.s.n.m. The National University's farm is in the state of Antioquia, in a small city named Rionegro (Figure 4 A, 4 B), 35 km away from Medellin, at coordinates 6º 07' 56'' N, 75º 27' 17'' W, as shown Figure 4 C. The weather conditions at the site were obtained from a nearby weather station. The average temperature was 16.2 ºC, with a relative humidity of 82% and an average rainfall of 2645 mm.

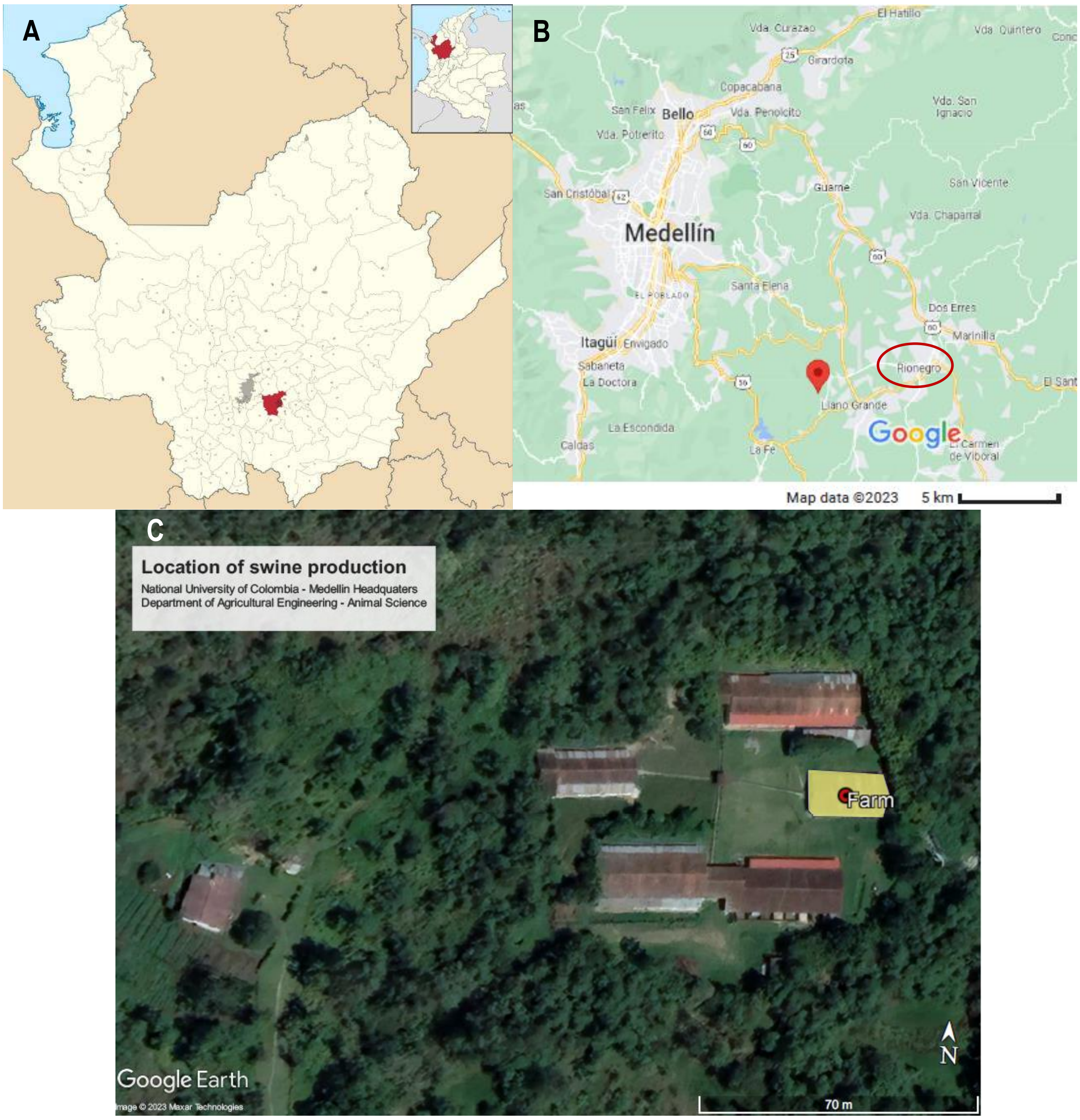

Figure 4. Location of the pig breeding barn of the National University of Colombia. (A) Location of the department of Antioquia in the upper right corner. Rionegro is symbolized in red within the department of Antioquia. (B) Farm and Rionegro location. (C) Swine facility location at the farm. Source: Google Earth, Google maps, 2023.

The facility where the experiment was conducted is a typical small and medium production facility in Colombia. It has no artificial lighting at night and no automatic air conditioning or ventilation system. The piggery has odor control windows that can be opened at the worker's discretion. Two pens were used; each pen was 2.41 m × 2.41 m and contained a 2 m continuous feeder and a nipple drinker. The pens were spaced 1.5 meters apart and a scale was installed between them to collect individual weight data three times per week. The pens were also elevated 0.5 meters above the floor. Figure 5 shows the general features of the facility and the experimental setup.

Figure 5. Swine production facility. (A) Raspberry Pi sensor collecting internal environmental conditions. (B) External facility features. (C) Males and females and their respective cages with the same environmental conditions. (D) Experiment setup for each pen, infrared light, Raspberry Pi sensor, camera ArdumCam OV5647 NoIR and Router.

The conditions of the building were the least technical imaginable, with an adequate shed for animal excrement, large windows for odor management, non-automatic windows that opened at the discretion of the worker. At night, there was an infrared lamp to warm the animals and no artificial lighting (Figure 5D). These light variations made it somewhat difficult to continuously analyze the images extracted from the night videos. The temperature inside the facility was controlled manually with the opening of the fixed window shades, and it is characterized by natural ventilation. The facility is oriented in a west-east direction as shown in Figure 5.

2.2 Experimental animals.

Weaned pigs of the PIC breed line were used after seven days of weaning, which means 30 days after birth. The average body weight of the pigs after weaning was 8 kg. At the beginning of each cycle, the weaned pigs were grouped by 10 females and 10 males each group in its own pen. The environmental conditions were all similar for both cages. The study was conducted in a conventional Colombian housing system for piglet rearing from about 8 kg to 40 kg. Throughout the experiment, the animals were kept in the pre-fattening stage, and at the end of each data collection cycle, they were moved to the fattening stage. The cages were placed 0.5 meters above the floor, according to Figure 6. In each pen, pigs were marked for identification in video recordings.

Figure 6. Set up and pigs at the beginning of each cycle. (A) Overall experiment conditions. (B) Pigs at seven days after weaning with marks in their backs.

2.3 Equipment and data collection

A low-cost system was implemented for real-time monitoring of pigs in the pre-fattening stage. An open Internet of Things (IoT) tool using ESP32 microprocessors and Raspberry PI were installed to collect environmental data (air temperature, relative humidity, pressure, radiation, and wind). The videos were recorded with cameras installed at a height of 1.5 meters from the slatted floor of the pig pen. The two cameras used were ArduCam OV5647 NoIR with a resolution of 1920 × 1080 pixels at 30 fps. It was installed three modules for measuring internal variables (inside of facility), external variables (outside of facility) and camera module. This study focuses on the use of artificial vision for data collected from the same authors as described in section 3.4 (Montoya et al., 2023). At the end of each cycle, the cameras were serviced because the pigs' feed produced a lot of dust that affected the quality of the video obtained for the next cycle. Videos of each cage were recorded from 6 am to 6 pm, with a duration of 1 minute per video. This means that 60 videos, each lasting 1 minute, were obtained every hour.

Four sets of trials were performed. Each trial consisted of 10 male and 10 female pigs and lasted 6 weeks to reach an average weight of 32 kg. Pigs were also manually weighed three times per week using handheld scales. Each pen had a data collection system using ESP32s and Raspberri Pi microprocessors. The ESP32 was programmed to collect microenvironmental data, and the Raspberri Pi microprocessor stored the videos, received the information from the ESP32, and then transmitted it wirelessly to a router. The information was accessed in a booth 50 meters away from the production site in real time via the Internet and Bluetooth connections. An ESP32 microprocessor-based environmental data collection module was installed on the outside of the building as shown in Figure 7C.

Figure 7. Equipment and data collection modules. (A) Internal module. (B) Weighing scale. (C) Outside module. Each internal module contained a camera that monitored males and females separately.

Figure 8 shows the general configuration of the experiment for one cage and one data acquisition cycle where the microprocessors and camera were installed. The installation for the two cages (males and females) of each cycle was completely identical.

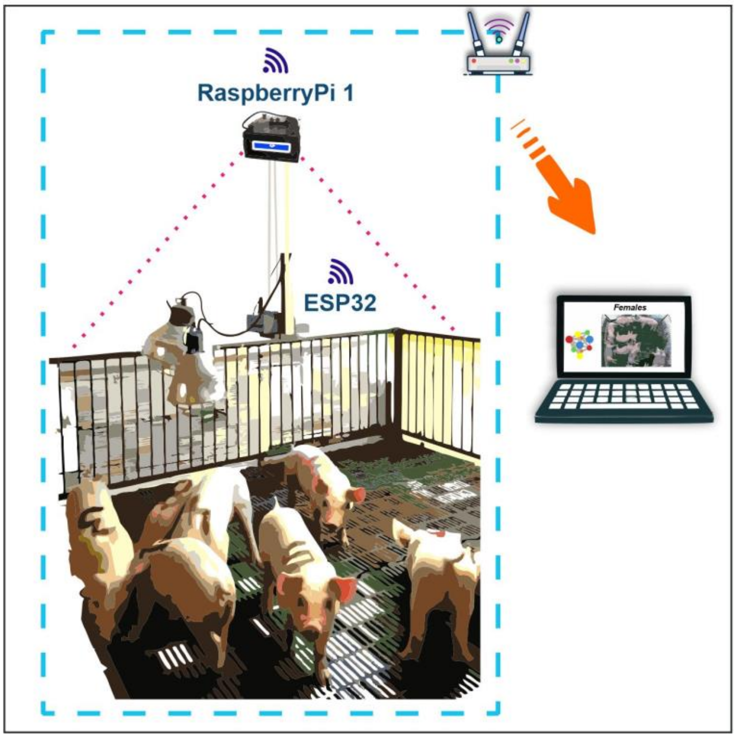

Figure 8. Experiment setup. Configuration of sensors and camera for one pen and one trial.

2.4 Automatic pig detection approaches

In the study conducted, the videos and sampled random images we acquired for labeling using the VGG Image Annotator (VIA) (Dutta & Zisserman, 2019). To ensure a diverse representation of different conditions, and to improve the model's detection power, the images that show very similar scenes (e.g., those sampled in close temporal proximity within the video) were excluded. Consequently, the images that were more representative of different conditions and scenarios were retained. The first step was the selection of the videos that corresponded to the days and hours of the manual weighing of the animals. Pigs were weighed in a manual scale (0 -1000 kg). A random sample of only 15 frames per video was taken from approximately 20 videos for males and 20 videos for females in a total of 4 cycles during the experiment. A total of 600 frames (300 for males and 300 for females) in this manner (Figure 99) were labeled. Subsequently, data augmentation techniques were applied to the labeled data before entering the data into the model. This involved randomly applying flips, rotations, crops, shears, exposure adjustments, and blurs to generate augmented images and increase the number of training examples for the model. In this way, the model is overfitted (Poggio et al., 2018), and if it finds an image that is not very good, it does not detect it, it analyzes images of any modification to detect the objects under any condition. The model must be general, synthesized data is produced based on real data. As a result, 1260 labeled data samples were obtained for training and for validation, 180 samples were separated, for testing model. The percentage of images used for training, validation and testing processes depends on the task to do. In this research, the purpose was only identifying pigs in different conditions, times and lighting, the model did not require such a demanding task to detect each individual. Therefore, the image sample does not need to be as rigorous when training, validating the model while adjusting the hyperparameters, and finally testing the final accuracy of the model with respect to the initial validation stage. There is no recommended split ratio for fitting the model, all the criteria depend on the task to be done, so in this case, testing with 14% of the total data was sufficient without any overfitting present. Each animal is contained within a polygon, and the polygon coordinates were recorded and used in conjunction with the images to train the convolutional neural network model for pig detection as shown by Figure 10.

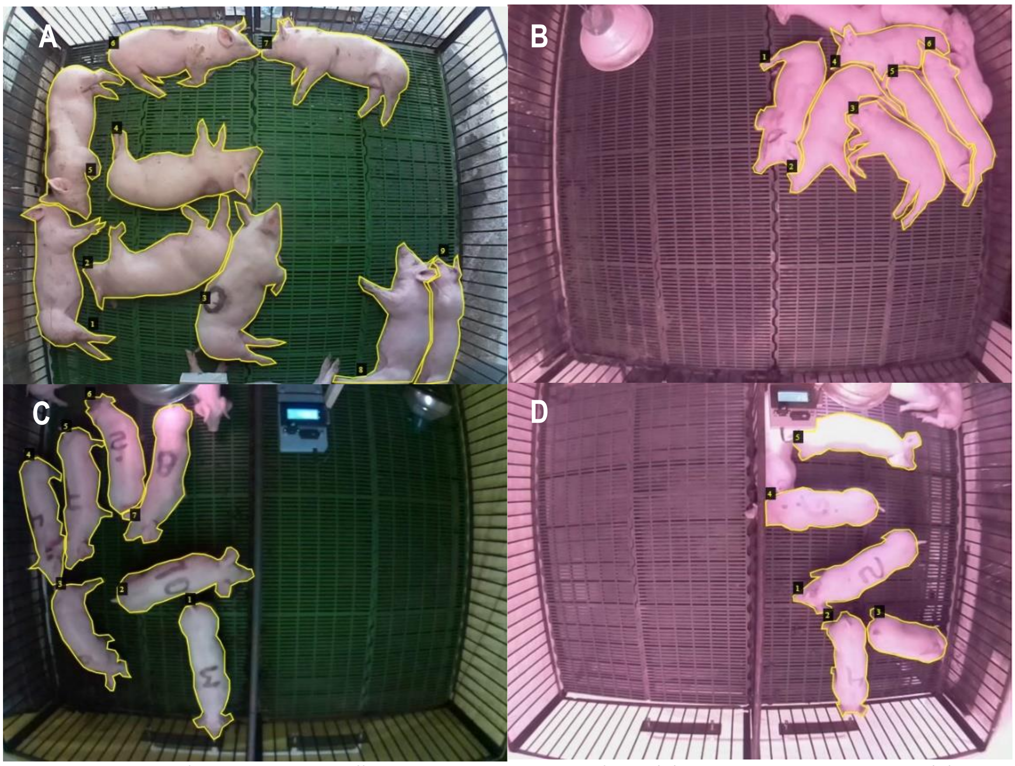

Figure 9. Labeled data samples of pigs in cages at different positions and times of day. (A) Pigs lying down in daytime. (B) Pigs lying down at night. (C) Pigs moving during the day. (D) Pigs moving at night.

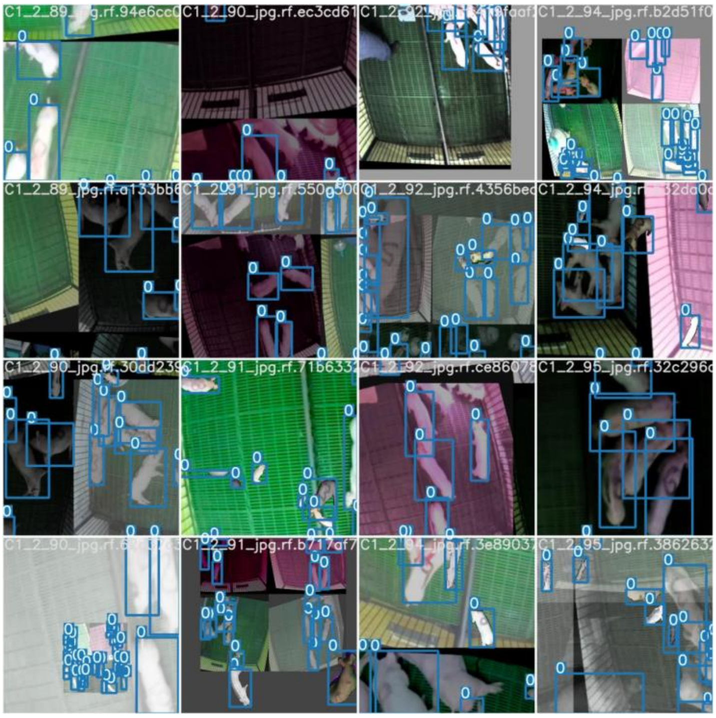

Figure 10. Data augmentation set for model training.

The deep learning model used to automatically detect pigs was a convolutional neural network based on the YOLOv7 algorithm (C.-Y. Wang et al., 2022). This artificial intelligence model divides the image into smaller sections called cells. Each cell is responsible for searching for objects using pre-defined fields and confidence values. To avoid duplicate detections, a special algorithm called Non-Maximum Suppression (NMS) is applied. NMS compares the detected objects and keeps only the most accurate and confident ones, removing all duplicates. This approach enables real-time pig detection, providing accurate bounding box coordinates and confidence scores in different environments, accurate segmentation of pigs in livestock environments.

The model was trained for 100 epochs, where each epoch represents a complete pass through the entire training dataset. A batch size of 60 was used during training. The batch size refers to the number of samples processed together in each iteration. It allows for efficient use of computational resources and facilitates the optimization process by updating the model parameters based on the error calculated from multiple samples at once.

To assess the performance of the model, the effectiveness of the validation data using different detection thresholds (0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.85, 0.9) was evaluated. Three commonly used metrics: precision, recall, and Mean Average Precision (mAP) were used. Precision measures the accuracy of positive classifications by calculating the proportion of correctly classified positive examples out of all examples classified as positive. Recall measures the ability of the model to identify true positive (T_P)

examples by calculating the proportion of correctly classified positive examples among all true positive examples. Finally, mAP is a metric primarily used in object detection, which calculates the average precision at different recall levels, providing a more comprehensive evaluation of the model's performance. All deep learning procedures were performed using Python 3.7 on a Linux (18.04LTS) machine with an Intel i7-9750H CPU (2.60 GHz × 12), 20 GB RAM, and an NVIDIA® GeForce® GTX 1660 (6 GB) Ti Max-Q GPU.

2.5 Evaluation metrics

To evaluate the performance of the model developed in this study, three common indicators in detection and segmentation models were used: Precision, Recall, and mean Average Precision (mAP). To define the metrics mentioned above, it is necessary to introduce four states that occur after predicting a test sample: True positive (T_P), False positive (F_P), True negative (T_N) and False negative (F_N). True Positive means all pigs detected that are truly pigs; False Positive means the model predicts objects as pigs, but they are not true pigs, it is an incorrect detection; False negative means the model does not detect the true pigs or is missing detections of pig and, True negative detects all elements that are not pigs (background). In this sense, True Negative is not applicable for object detection and segmentation because it detects the pig image as background, which is equivalent to not detecting anything.

Precision measures the proportion of items that system has been successful in selecting (Mannning & Hinrich Schütze, 1999), as shown Equation (1), all True Positives out of total positive detections, in other words, precision measures the model's quality. On the other hand, Recall measures model's ability to detect true positives (pigs detected correctly) out of all predictions (ground truth), in other words, is defined as the proportion of the target items selected by the system (Mannning & Hinrich Schütze, 1999) as shown Equation (2). The value ranges for precision, Recall are from 0 to 1.

$$Precision = \frac{T_p}{T_p + F_P} \qquad (1)$$

$$Recall = \frac{T_P}{T_P + F_N} \qquad (2)$$

Mean Average Precision, hereinafter mAP, needs to introduce the first Average Precision (AP) concept. Average Precision is the area under the precision-recall curve for each class, and mAP is average over all predicted classes, incorporating the trade-off between precision and recall and considers

False positives as well as False negatives, used to evaluate the robustness of object detection models, as shown in Equation (3), (4)

$$AP = \int_0^1 precision(recall)\, d(recall) \tag{3}$$

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i \tag{4}$$

Where n, is the number of classes, AP_i is the average precision class i . In this research only one class was evaluated labeled as “pig” as shown Figure 9.

3. RESULTS

3.1 Testing results

The precision-recall curve (Figure 12) joins the trade-off of both metrics mentioned before and maximizes their effect on the model’s performance, allowing a better idea related to overall accuracy obtained.

The evaluation metrics (Precision, Recall, and mean Average Precision) of individual detection remained consistently high throughout the model training, as shown in Figure 11A.

The Deep Learning model showed high performance in pig individual detection. Furthermore, when tested on the validation dataset at various detection thresholds, the model continued to demonstrate remarkable performance (Figure 11B). Despite crossing and overlapping between pigs, animals were reliably detected with high accuracy (values from 0.9 and 1.0), as shown in Figure 11C. In terms of accuracy, the model predicted every pig after 30 epochs, which supports the 180 data for testing mentioned above.

These results highlight the robustness and effectiveness of the developed model in accurately detecting pigs in challenging scenarios. The high precision indicates that most positive classifications made by the model were correct, minimizing false-positive detections. High recall indicates that the model successfully identified a large proportion of truly positive examples, ensuring minimal false-negative errors. The sustained high mAP values further validate the overall performance of the model, considering the trade-off between precision and recall at different recall levels.

Such reliable pig detection capabilities hold promise for various livestock management applications, enabling precise monitoring to optimize farming processes and ensure animal welfare.

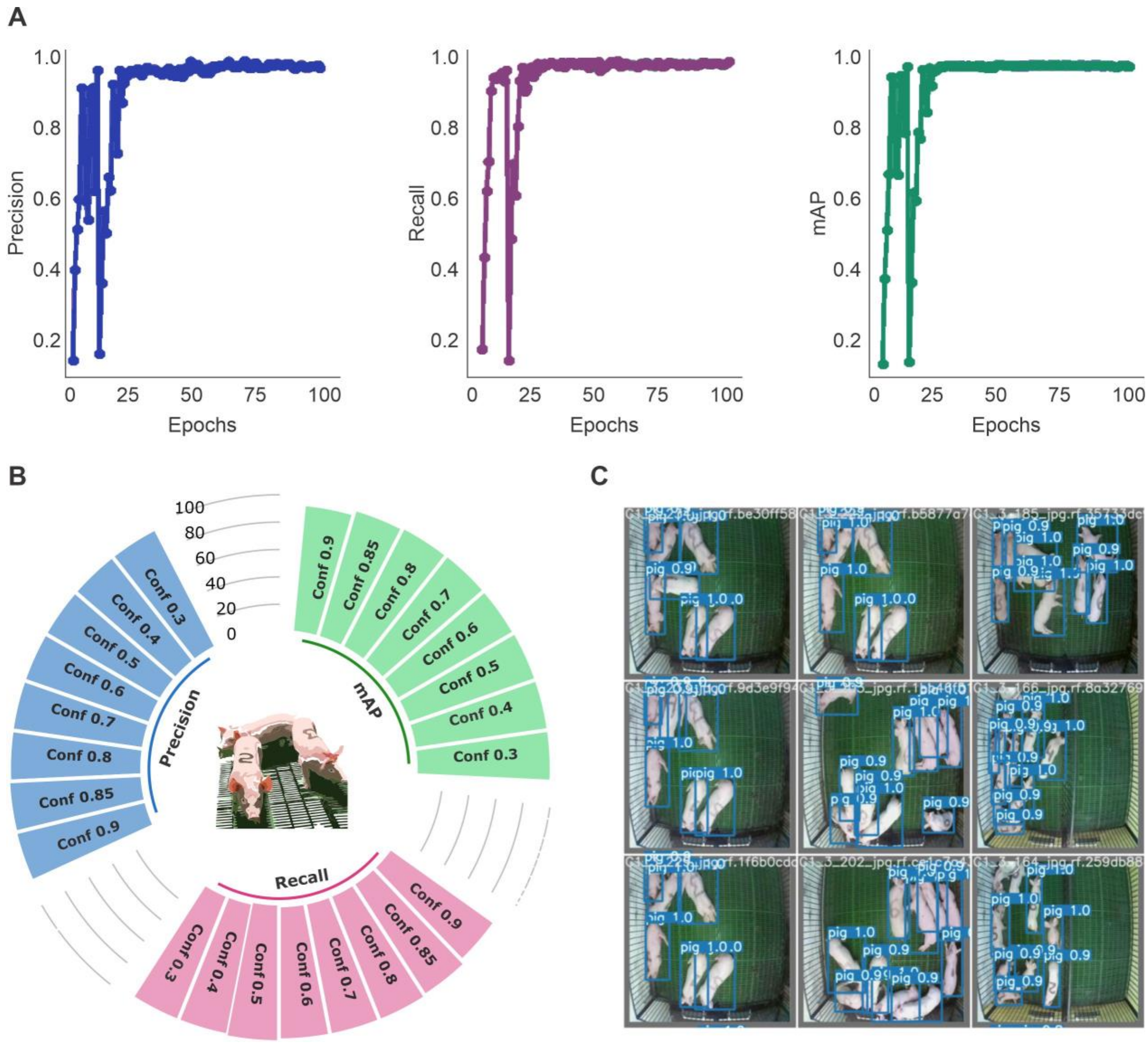

Figure 11. Performance evaluation of the convolutional neural network model for automatic pig detection in livestock. (A) Scatter plots showing the performance metrics - precision, recall, and mean average precision (mAP) - during the 100 training iterations over the epochs. (B) Performance metrics observed during the validation of the model using different confidence thresholds (indicated by the values inside the bars). (C) Visual representation of pig detection by the model applied to random images. Each detected animal is marked with a bounding box, along with the corresponding confidence score indicating the reliability of the detection.

For precision - recall curve (PR curve), Figure 12 shows the tradeoff between precision and recall for several thresholds. The overall performance is better when the convex curve becomes more convex. The area under curve is mAP representing a 98.8%, which denotes a low false positive rate, a high precision of 97.3% and low false negative rate, which means a high recall of 98.4% at 0.5 of confidence.

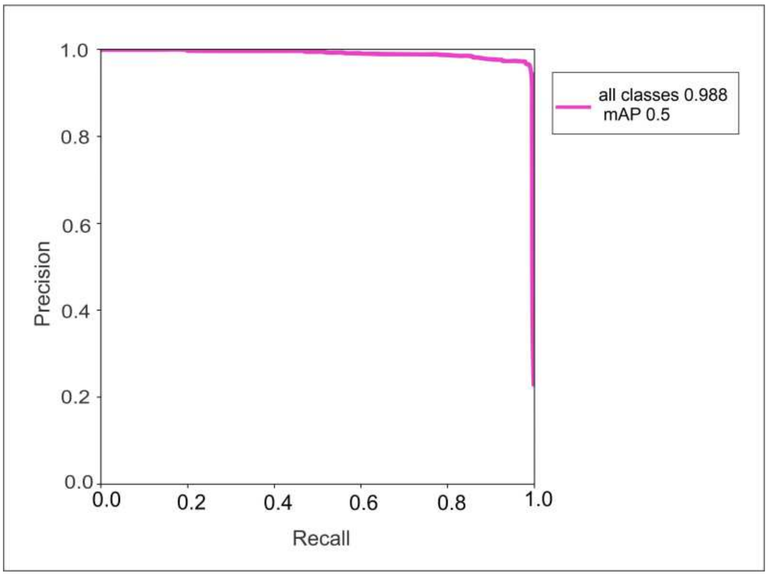

Figure 12. Precision vs Recall curve for all detections at mAP 0.5 of confidence.

4. DISCUSSION

The proposed methodology tested the ability of the neural network based on the YOLOv7 algorithm to identify each individual in a group housing system of pigs in the weaning phase and housed under real conditions of a pork production construction. This method reached a precision of 98.3% with a detection threshold of 0.9, and a recall rate of up to 98.5% with a detection threshold of 0.85 as shown Figure 11B. It was obtained a higher precision than authors (Zhang et al., 2019) which achieved a precision of 94.72% and recall of 94.74% with Single Multibox Detector (SSD). They detected and tracked multiple pigs under different image conditions, such as shape deformations and light fluctuations. The authors used artificial light between the hours of 7:30 and 16:00, combined with natural light from two small windows. This method, on the other hand, obtained higher precision recording videos only in a natural light condition compared to (Zhang et al., 2019).

Although this method was more accurate, the speed of the detection was lower than (Zhang et al., 2019). They implemented three CNN detection architectures, but the fastest was the Single Multibox Detector (SSD) with a speed of 42 milliseconds per frame (Zhang et al., 2019). In this study a speed of 48.3 milliseconds per frame was achieved and could be considered that speed of detection can influence the quality of image processing, and even though the architectures compared are different, this is an important indicator to evaluate the model performance.

Authors such as (Sun et al., 2019), obtained a higher recall rate than this research, using a sliding window method on pig detection. They reached a recall rate of up to 99.21%, using BING+PCANet, Faster

R-CNN and YOLO, but their method has a low computational efficiency's disadvantage which depends on window size and ratio on manual design (Sermanet et al., 2013), and they reached the recall rate mentioned, compared to the first YOLO version. By contrast, our study adopted YOLOv7 algorithm which uses around 36.9 million parameters, 43% less in computational requirement, compared to previous versions such mentioned and is faster than most state-of the-art detection networks, achieving a real-time processing without compromising accuracy (Hussain, 2023; C.-Y. Wang et al., 2022).

Another approach is using different camera perspectives as proposed by Riekert, M., Klein, A., Adrion, F., Hoffmann, C., & Gallmann, E., (2020) that used The Faster Region-Based Convolutional Neural Network (Faster R-CNN) for object detection using video images from pig fattening and pig rearing at different camera positions. They trained two models (pig position and posture and pig positions only). For the pig position model on pig rearing, they obtained the highest Average Precision (AP) of 76.8% when the camera was located at the top of the pen, compared to front and back cameras. In this sense, the present study obtained a higher Average Precision than authors mentioned, for the same setup conditions (pig rearing phase, with top camera setting), but using a different algorithm, obtaining a rate of 97.5% of AP, in a confidence of 0.85.

Another reason for choosing to conduct this study with pigs in the weaning phase is that it is more difficult to detect individuals in this phase due to their behavior. As shown by (Riekert et al., 2020), the percentage of AP was lower when evaluating the weaning phase than the fattening phase, due to the limitation of tightly grouped piglets. In the fattening phase, each animal is more isolated from the others, which allows a better recognition of each individual. In the weaning phase, the animals are still adapting to the internal environment, so it is more common to find them in agglomerations inside the cages which leads to tracking errors and problems of segmentation. To tackle this adaptation problem, an infrared camera was implemented to ensure the internal temperature of piglets' pens for the first week of each cycle.

According to Figure 12 and Figure 11B when Recall increases, False Negative decreases, it means to decrease the quantity of pigs not detected by the model. When Precision increases, False Positive decreases, it means that decreases the number of objects detected as pigs but are not pigs. For Precision score, with a confidence of 0.9, 98.3% of detected items were really pigs, and 1.7% was false positive. In the case of Recall, with the same confidence, 93.9% of elements were correctly detected and 6.1% were false negatives. In this sense, the particular purpose of this study is prioritizing precision, with a focus on minimizing false positives, i.e., to detect true pigs even if, are missing one of them. In contrast, recall focuses on minimizing that potential pigs are not missed.

This study obtained a similar precision compared to (Yang et al., 2018), but the authors used Faster R-CNN, and even though the authors reached 95% of the individual pigs identified correctly, this network is still far from being a real-time system (Zhang et al., 2019), as the one proposed in this research.

The results obtained in the performance of the model confirm the importance of using a database with the greatest possible variability in terms of geometric transformations of the image, as mentioned by (Biase et al., 2022; Chatfield et al., 2014; Srinivas et al., 2016). In this way, the model used in this research became more realistic and, when images with different lighting settings, perspective changes or even image angles are introduced, the model is able analyze such variations and accurately detect each of the animals in their cages.

Finally, to detect accurately individuals in a group play a critical role in subsequent real-time processes such as behavior analysis, feeding and weight prediction. Therefore, ensuring a high precision in this stage can guarantee in a preliminary analysis, a high precision in other variables to assess in future research.

5. CONCLUSIONS

The recognition method of individual piglets in two cages in the weaning stage, using the Yolov7 algorithm was proposed in this study. The method was able to analyze images with different geometric transformations, using synthetic images produced from real images (data-augmentation) to identify slow weaning pigs and to make appropriate decisions in the facility. This study allowed an accurate detection of 98.3% of pigs housed in groups in the weaning phase. The weaning phase is a stage in which pigs are in constant adaptation to different thermal conditions, a change from liquid to solid diet, which is why it is more challenging to detect each individual pig in a cage, because they are all together maintaining their ideal body temperature. This is why it is considered a critical phase of pig production in the whole productive chain, because the success of a weight in fattening pigs depends mostly on the management given in the weaning phase.

What has been developed here can be used as a basis for future behavioral analysis, animal posture detection, comfort analysis and animal growth monitoring, or even classification by sex in large groups or identification of animals in different stages of growth. The model used in the present study obtained a high accuracy in the detection of animals under real conditions of medium and small pork production in Colombia in one of the Departments with the highest pork production in the country.

This study was a fundamental idea to pig production tracking and can be used in future research to enhance specific tasks in production systems, such as behavior tracking and environmental conditions. Due to the experiment as a real time application, the decision-making process in pigs or even other animal productions will be encouraged in terms of time optimization or making appropriate decisions according to current needs.

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CHAPTER 3

PIG WEIGHT PREDICTION OF MALES AND FEMALES IN WEANING STAGE

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ABSTRACT: Accurate weight prediction can enhance profitability in animal husbandry and reduce human efforts to weigh individuals which implies time demanding, animal stress and human errors. The objective of this chapter was to evaluate and implement an automatic weight pig prediction system based on convolutional neural networks. Processing optimization and validation were obtained from a manual recorded weight, comparison between three pre-established architectures (MobileNet, ResNet50, DenseNet121) and an own created architecture (CustomNet). The best performance was achieved by the DenseNet121, and four optimizers were tested with this neural network (SGD, RMSprop, Adam and Nadam). Three cases were evaluated (females and males together, females only, and males only). The best model was represented by DenseNet121 and Adam optimizer, obtained a coefficient of determination of R^2 of 0.98 for two first cases, and for males only reached a R^2 of 0.96 with a higher dispersion between weights. This model achieved high performance without controlling internal conditions as group-housed, lighting or animal postures in a crucial phase in pig production.

Keywords: Deep Learning, optimizers, pre-fattening pig production, DenseNet121, Adam optimizer.

1. INTRODUCTION

Individual weight determination in pig production systems is one of the most important practices in pig management (Bhoj et al., 2022), and efficient production depends on the weight gain of each animal in the final stage of rearing (Bhoj et al., 2022; G. Li et al., 2022). In supply chain planning in the pork industry, it is necessary to have an accurate pig size estimation to avoid higher operating and inventory costs (Apichottanakul et al., 2012).

Liveweight is an important indicator of the animal's growth, health, and readiness for market (Kongsro, 2014) and individual pig weight and growth affects the productive dynamics of the installation as time of growing, feed costs which accounts for 60% of total production cost (Bhoj et al., 2022). Other factor is animals' fear of people, which can be a major source of stress, may influence their welfare, behavior, and cause much lost production (Rushen et al., 1999). Therefore, precision in predicting weight pig aid to decision making in all possible scenarios in a productive chain.

Methods like Machine Learning have been developed to predict the weight of livestock animals accurately. For instance, (Liu et al., 2020) estimated weight in cows using distances between joints on the cow's body, and other authors have found a relationship between weight and volume of pig body (H. Chen et al., 2023; Schulin-Zeuthen et al., 2008) and body weight and top-view body area of pigs (Schofield et al., 1999). However, (Y. Wang et al., 2008) claim that between physical features extracted from pigs' images (width, length, perimeter, area), and correlated with pig liveweight, area has the best correlation and has become the mainstream way to weigh pigs. However, machine learning methods have a challenge related to the ability to perform well on previously unseen inputs called generalization (Goodfellow et al., 2016).

(H. Chen et al., 2023) constructed a multilayer Radial Basis Function (RBF) network to predict weight of sows and boars from 150-190 days-age by means of one-dimensional parameters measurements (e.g., chest, abdomen, and waist) body circumferences, length, and height. They relate weight to the most representative one-dimensional parameter, concluding that it is necessary to reduce the number of parameters (body dimensions) to find the most relevant parameter for weight prediction. However, this method required human-pig contact and a specific posture of pigs to measure with a high accuracy and confirms the need to develop more generalized prediction methods applicable to different production scenarios.

There are different ways to measure the pig mass using artificial neural networks, one of them was a walk-through system proposed by (Y. Wang et al., 2008) where animals could walk through a passage while a camera was imaging them and ensuring a high contrast between background and pigs. However, this method was developed to weigh only one pig at a time as well as (Kongsro, 2014),where infrared-light was used to take pig images and get depth body information of animals. The IR sensor eliminated the errors related to animal color and lighting conditions. However, the authors were conditioned by animal posture and when it was not appropriate, the accuracy decreased.

Following the methodologies already mentioned, it is important to indicate that the prediction of weight by machine vision is conditioned to factors such as: proximity of individuals in cages which affects processes such as detection of body edges and position (standing or lying animals). For the case of individual detection, algorithms based on Gaussian Mixed Models, Convolutional Neural Networks, Adaptive Thresholding o You Only Look Once v3 (YOLOv3) and Simple Online Real-time Tracking (SORT) have been used on 2D images by (Guo et al., 2015; Jensen et al., 2021; Zhang et al., 2019) Developing an algorithm that allows the identification of each individual and differentiates the positions (lying or standing), is an alternative to estimate the weight of animals with as little error as possible.

Several authors state that there is a high correlation between the weight of animals and their physical dimensions, such as area and volume (Cominotte et al., 2020; G. Li et al., 2022; Minagawa & Ichikawa, 1994). This allows the weight of animals to be determined indirectly, using image analysis methods, which identify their physical characteristics, by means of 2D images. However, the detection of these characteristics is conditioned to the position of each of the animals and their proximity to other individuals; lighting stimuli and stress represented by the climatic conditions of the environment.

There are studies that determine the weight of pigs in the late growth phase individually (Schofield et al., 1999; Wongsriworaphon et al., 2015); other studies determine position characteristics of pigs in the early growth phase at different temperatures (Nasirahmadi et al., 2019) and studies such as those by (Jensen et al., 2021) that individually identify nine-week-old growing pigs in groups of 7 animals. However, weight prediction in the early growth phase of pigs requires a more detailed approach to the body dimensions of each individual to optimize weighing processes, identify slow-growing animals, and obtain the highest production yield.

Furthermore, Schofield et al., (1999) and Wongsriworaphon et al., (2015) used techniques such as vector-quantified temporal associative memory (VQTAM) and artificial neural networks (ANN) to determine the weight of pigs in the final growth phase by analyzing individual images with 2D cameras. However, in pig production systems, animals are not isolated from each other and therefore it is essential to develop algorithms that can identify each individual, even when housed in groups.

(Hou et al., 2023) predicted cattle weight with 3Ddeep learning model PointNet++, where point cloud data and light detection and ranging (LiDAR) sensor were used to extract the body measurement point and then, the authors calculated body weight (BW) using Johnson's method that relate body size (chest girth, body length) and weight.

Finally, the objective of this chapter was evaluated and implemented an automatic weight pig prediction system based on convolutional neural networks, through processing optimization and validation with manually recorded weights. Differences in weight gain between males and females and the accuracy of the models used in each case, were evaluated.

2. MATERIAL AND METHODS

2.1 Sampling and weighing of pigs.

The animals were weighed, and the weights of each animal were documented for training the model in subsequent steps. Fifteen images were selected for each video, considering different times of day, positions, and lighting. Animals were weighed three times per week and the selected images correspond to the same weighing days. The procedure was repeated identically for males and females.

2.2 Image Acquisition

Using the deep learning model Yolov7, the pig detection was conducted, bounding box delineation, and subsequently a total of 2714 random images of pigs were obtained, encompassing both males and females, with 1392 images corresponding to females and 1322 to males. Subsequently, these images were resized to a resolution of 124 × 124 pixels and associated with the respective pig weights obtained from an analog scale. For the training of deep learning models aimed at predicting weights, 80% of the data was allocated, while the remaining 20% was reserved for model evaluation and testing.

2.3 Weight prediction based on animal images.

In this study, convolutional neural network (CNN) models were trained and applied to estimate the weights of pigs based on images of the animals under different random conditions sampled on the facility. The use of convolutional neural networks helped the model used in the study learn to predict the weight of each animal based on actual weights collected at the facility, eliminating the need to manually extract morphological characteristics such as body length and width of pigs.

Pig's weight estimation models, considering data from both males and females, were developed, as well as separate models for females and males. This allowed to assess whether the automatic weight estimation performance varied with the sex of the animals. **Error! Reference source not found.** shows the flowchart depicting the Deep Learning procedures to predict pig weight.

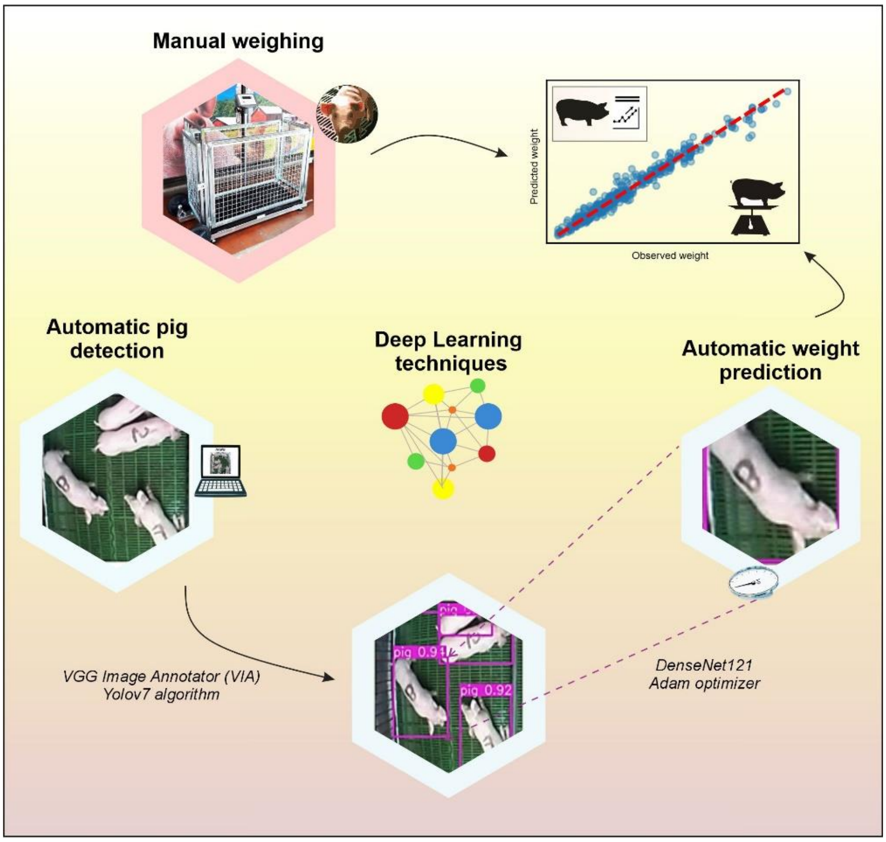

Figure 13. Flowchart depicting the deep learning procedures proposed to estimate the weight of pigs automatically. Automatic animal detection using bounding box, cropped image of animals of interest and weight prediction for each animal.

To prevent overfitting, a condition where the model has a good learning and performance on the training dataset, but its performance on the test dataset it is not good (Goodfellow et al., 2016), data augmentation techniques were applied, which included random image rotations up to 30 degrees, as well as 20% variations in height, width, shear, and zoom. Additionally, half of images were horizontally flipped, and the nearest-neighbor strategy was used to fill in newly created pixels resulting from rotations or shifts in width/height.

Fine-tuning was performed by training the entire network with randomly initialized weights. Fine-tuning is a strategy to use the weights of an existing network, when the new dataset (in this case, pig sample images) and the domain of the pre-trained model are similar; all of which avoids starting a new model from scratch (Wei et al., 2018). Multiple pre-established networks were evaluated, including MobileNet, ResNet50, DenseNet121 (Densely Connected Convolutional Network), and an own custom architecture named (CustomNet). The architecture defined for Customer is in supplemental material S1. The training and validation processes were monitored by measuring loss and Mean Absolute Error (MAE) to identify the best-performing models. Training time per epoch and examined overfitting, calculated as the ratio of test MAE to validation MAE, were also assessed.

The classification layer added on top of these pre-established networks consisted of three dense layers with 64, 32, and 1 unit(s) per layer, respectively. An exponential linear unit (ELU) activation function was applied to speed up the deep learning process, and the batch size was set to 68. To minimize overall loss and improve model's accuracy, three optimizers were compared on training and validation process. The Adaptive Moment Estimation (Adam) optimizer and employed mean_squared_error as the cost function (difference between the predicted value and the actual value), were selected. During fine-tuning, the same data augmentation parameters as those used during hyperparameter optimization of the custom convolutional network were employed. To prevent overfitting during training and validation, a callback that halted training after 15 successive epochs without validation MAE improvement was implemented and loss and mean square error for both training and validation and recorded training time per epoch were monitored.

Following the determination of the best deep learning architecture, various optimizers (SGD, Adam, Nadam, RMSprop) were tested, all trained on combined male and female data. After identifying the optimal architecture and optimizer, weight prediction performance across the entire dataset (males and females), females only, and males only; were compared. Performance evaluation involved comparing the automatic weight estimations generated by the models with manually observed weights on the scale. The coefficient of determination (R^2) and the mean absolute error (MAE) of the automatically estimated weights against the manually recorded weights, were calculated.

All deep learning procedures were conducted using Python 3.7 on a Linux (20.04LTS) machine equipped with an Intel i7-9750H CPU (2.60 GHz × 12), 20 GB RAM, and an NVIDIA® GeForce® GTX 1660 (6 GB) Ti Max-Q GPU.

2.4 Evaluation metrics

To evaluate the performance of the model developed in this study, were used Mean Absolut Error (MAE) and Loss to identify the error rate in the prediction of animal weight. The MAE score is measured as the average of the absolute error values (Schneider & Xhafa, 2022). During training, the training time per epoch was measured to see which model was faster. Overfitting was also measured to analyze the generalization capacity of each model Figure 14 and optimizer Figure 15. The overfit was calculated as follows: ratio of the average test error to the average validation error.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Actual - Predicted|$$

Accuracy was calculated as follows:

$$Accuracy\ (\%) = \left(1 - \frac{LW_{obs} - LW_{pred}}{LW_{obs}}\right) * 100$$

Where, LW_{obs} is live weight observed or measured in scale, LW_{pred} is live weight predicted. In Section 3.4, the accuracy was calculated with a Mean of live weight observed and predicted in three cases (females and males together, females only and males only).

3. RESULTS

3.1 Comparative architectures

Were evaluated three pre-established networks, including MobileNet (Howard G. et al., 2017), ResNet50 (K. He et al., 2015), DenseNet121 (G. Huang et al., 2018), and an own custom architecture named (CustomNet). According to Figure 14A, all architectures were evaluated with Loss and MAE metrics in their training and validation process and time processing and overfitting were also determined. The overfitting value was also the lowest in CustomNet compared to all other established architectures. All the pre-trained networks have an overfit, it is represented when Test MAE curve is over Training MAE, it means that the model's is learning well, but when it takes a new sample of unseen images, it does not predict well and has a high MAE value in the first epochs. However, as the epoch increases, the overfit decreases and the test curve is close to the training curve (Figure 14B, C, D). The customer network has no overfit, but the MAE is 4.22 as shown in Figure 14A, 14E, and the other models have an error of less than 1.

According to Figure 14A, can be identified the loss (difference between the predicted and actual values), and the MAE metric for training and validation processes for all networks. For training the best performance in those metrics was ResNet50. However, it is important to compare the performance of training such as validation to detect the lowest overfit. In this sense, DenseNet121 is the second-best network in training, and the best network performance in validation, obtaining the lowest overfit of all three pre-established networks. Although DenseNet121 does not have the lowest time of processing, the selection criteria for the best network were the overall performance on the training and validation set.

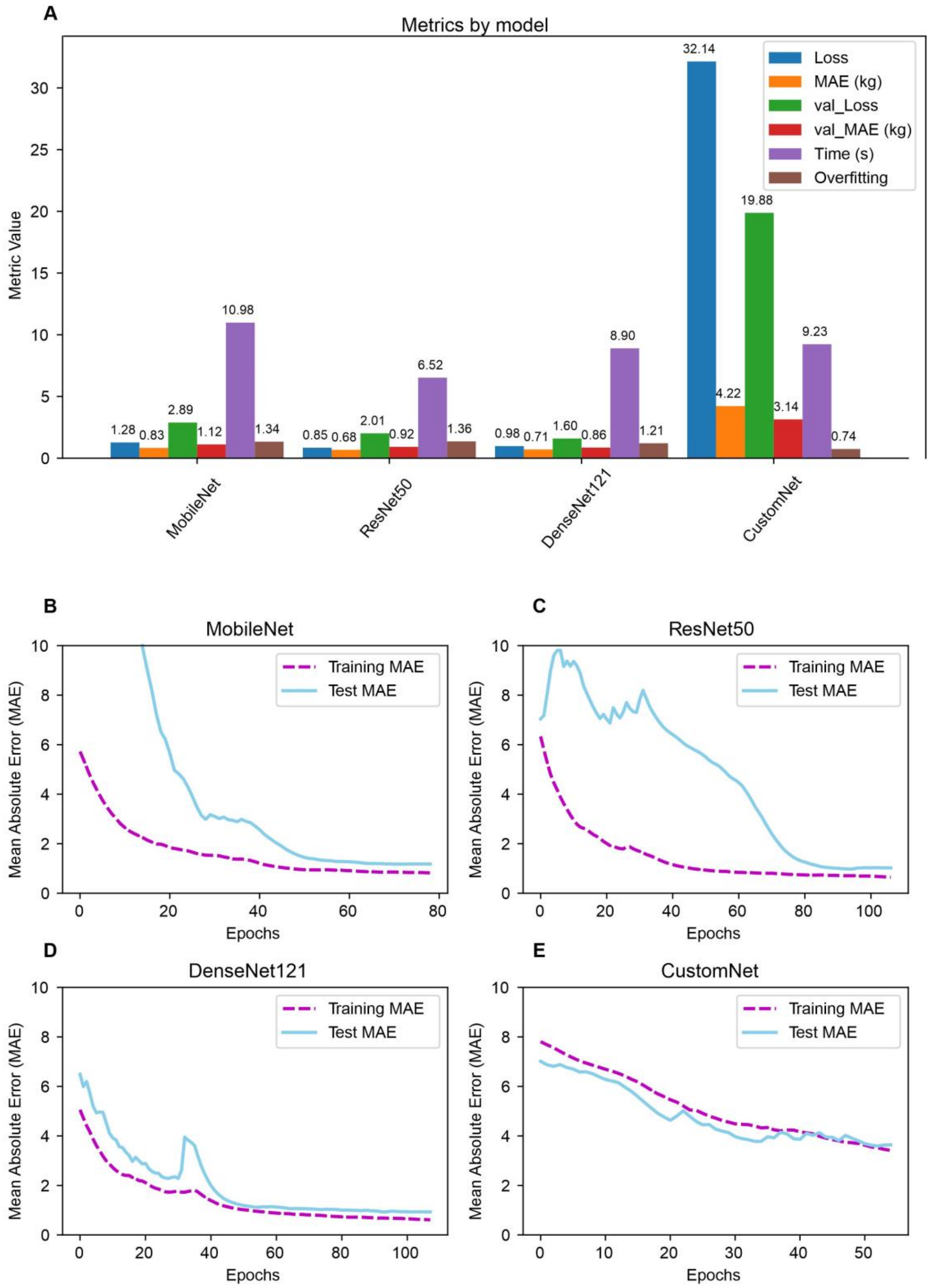

Figure 14. Performance evaluation of different deep learning models for automatic measurement of pig weights from RGB images. (A) Variable values obtained during model training. The training time per epoch is measured. (B) MAE for training and testing on the MobileNet model. (C) MAE for training and testing on the ResNet50 model. (D) MAE for training and testing on the DenseNet121 model. (E) MAE for training and testing on the CustomNet model.

Analyzing MAE metric in Figure 14B, it is evident that MobileNet had a high overfit in the first 20 epochs with a MAE over 10 kg in test curve, and training curve starting around 6 kg. The difference between training and test curve began to decrease and stabilize around the 50th iteration. The ResNet50 (Figure 14 C) reached a MAE value of 10 kg for test the curve and its behavior varied considerably around 40 epochs until it stabilized after 70 iterations. This is reflected in the highest overfit of all the proposed networks (Figure 14 A). For DenseNet121 (Figure 14D) the difference between the training and test curve had an almost stable behavior and less than 2 kg approximately from epoch 0, except for iteration 38 approximately where there is a peak that indicates an increase in the error, but it is part of the learning process of the network. However, the behavior of these two curves stabilized after iteration 45 approximately, maintaining the lowest overfit of all the preset networks as Figure 14A shows.

For all the pre-established networks, a common event occurs where the metrics (loss and MAE) for training are always lower than the same metrics in the validation. For CustomNet, the metrics in validation have the opposite behavior compared to the other three networks. The validation loss and MAE are lower than the training process, which is reflected in Figure 14D where the training curve is above test curve for the first 40 epochs approximately. Although CustomNet's overfit is lower than all the networks mentioned, it maintains the highest MAE in both validation and training. Therefore, of all the architectures tested, the DenseNet121 network achieved the best performance with the lowest MAE, validation loss and overfit and then, was selected to proceed to the next steps.

3.2 Comparative optimizers

Several optimizers were tested with the chosen model, DenseNet121. An optimizer is an algorithm that updates the network weights. The network goes through all the data in an iteration and tries to get the weights right. It sees if it's wrong and then updates all the weights again. In this sense, optimizers drive the cost function to a very low rate until it reaches a global minimum and minimize the error between input data and actual output (Goodfellow et al., 2016; Schumacher & LaBounty, 2023). There are several algorithms to adjust the model's parameters during the training process to minimize cost function, but in the study, four optimizers based on the Gradient Descent algorithm were tested that change some details in the performance (Figure 15).

Figure 15A shows all optimizers analyzed (Stochastic Gradient Descent or SGD, Root Mean Square Propagation or RMSprop, Adaptive Moment Estimation or Adam and Nesterov-accelerated Adaptive Moment Estimation or Nadam). The SGD optimizer, for instance, is a variant or Gradient Descent algorithm that uses the chain rule derivative of all the neurons in the network. It derives thousands of multidimensional parameters until it finds the minimum of the function of all the neurons and reaches the maximum of the function where it will have the smallest error. In other words, it updates the model parameters one by one until to find the minimum error which means its low computation speed (Saranya et al., 2022).

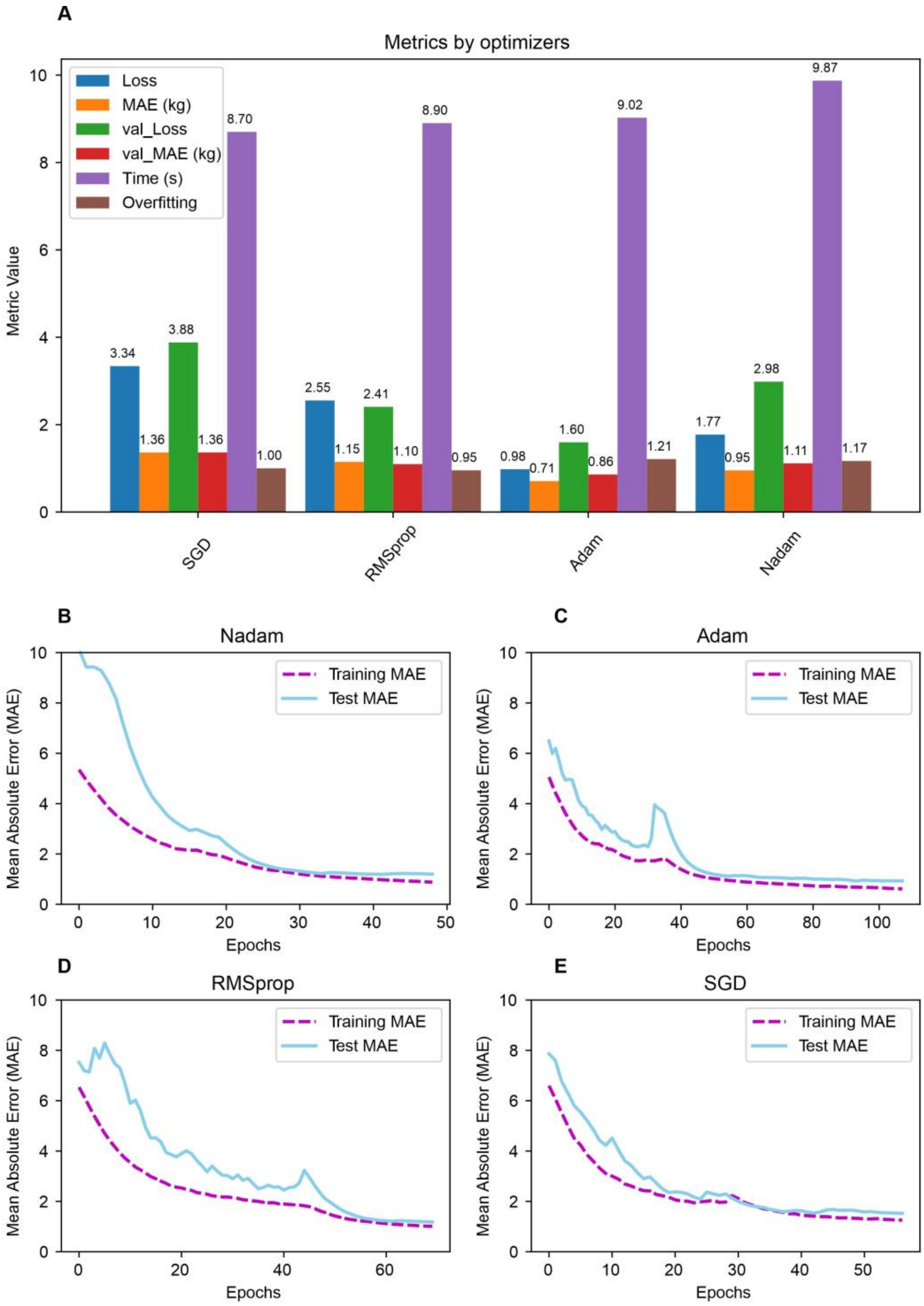

Figure 15. Performance evaluation of different optimizers (SGD, Adam, Nadam, RMSprop). The model architecture used to test the optimizers was DenseNet121. (A) MAE for training and testing on the Nadam optimizer. (B) MAE for training and testing on the Adam Optimizer. (C) MAE for training and testing on the RMSprop optimizer. (D) MAE for training and testing on the SGD optimizer.

On the other hand, RMSprop has an automatically learning rate and decay rate of each parameter of the model, using a moving average of the squared gradients, which stabilizes the learning process and avoids oscillations in the optimization trajectory. Therefore, RMSprop uses an adaptive learning rate instead of treatin the learning rate as a hyperparameter, then the learning rate changes over time. (Schumacher & LaBounty, 2023) . Adam is a method that only requires first-order gradients by using a minimal memory, fast convergence, and computes individual adaptive learning rates for different parameters (Kingma & Ba, 2014; Schumacher & LaBounty, 2023). Lastly, Nadam combines Adam algorithm and Nesterov accelerated gradient by calculating the adaptive learning rate and momentum for each parameter and then, updating the parameters in the direction of gradient by using Nesterov accelerated gradient (Schumacher & LaBounty, 2023).

Analyzing the performance of all optimizers, four metrics were assessed to identify the best optimizer. Figure 15A shows loss, MAE, the validation loss (val_loss), validation MAE (val_MAE), time and overfitting of each optimizer. The Adaptive Moment Estimation was selected among the other three optimizers (Figure 15B) as the better optimizer due to its lowest MAE and loss in training and validation performance and even though the time processing and overfitting were not the lowest among all optimizers, but the more important metric to select the best performance was MAE and loss.

As the iterations in the learning process progressed, the performance curve in training and testing for each optimizer varied. Figure 15B shows the Nadam optimizer, with a marked difference in the Mean Absolute Error at the beginning of the iterations, higher than 5 kg, and the error curve in training and testing are getting closer after approximately 20 iterations.

In the case of the Adam optimizer (Figure 15C), the training and test curve have a difference lower than 2 kg approximately at the beginning of iterations. For RMSprop, Figure 15D shows the lowest overfit compared to all optimizers, but its MAE is higher than Adam optimizer. For SGD optimizer, Figure 13 E shows training and test curve start with a MAE of 8 kg and above 6 kg approximately, values higher than Adam optimizer for the same epochs.

3.3 Weight prediction

Of all the networks evaluated, the DenseNet121 network was tested with all the optimizers and the optimizer with the lowest error was selected. With the defined network and optimizer, it was possible to automatically estimate the weight of males and females with high accuracy. Figure 16 shows the fit of the predicted weight results with respect to the weight measured by the DenseNet121 network model and the

Adam optimizer. Figure 16A shows the results of evaluating the model with the Adam optimizer considering males and females together, females only (Figure 16C), and males only (Figure 16E).

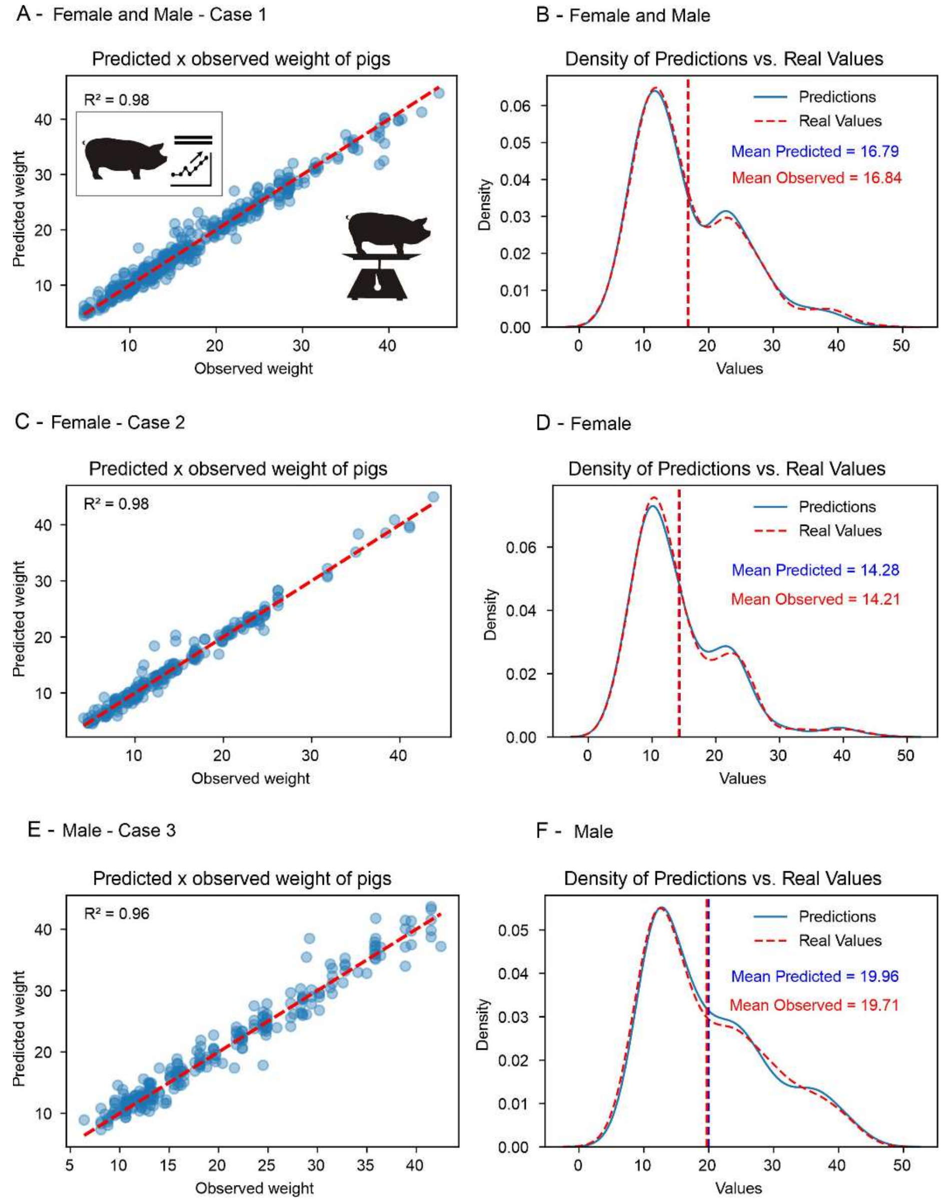

Figure 16. Measured weights versus estimated weights over six measurements weeks of two pens with ten pigs per pen in the validation experiment. (A) Measured weights versus estimated weights of females and males together. (B) Density of predictions versus real values for females and males together. (C) Measured weights versus estimated weights of females only. (D) Density of predictions versus real values for females only. (E) Measured weights versus estimated weights of males only. (F) Density of predictions versus real values for males only.

The blue dots in Figures 16 A, C, E, are the predictions made by the model used, and the red line shows ideal behavior if all the predicted weights were equal to the measured ones, but this is not the case because the model's accuracy is not 100% precise. In the case of the points were all on the red line, it would indicate that the model is overfitting. In all three cases analyzed (Females and males together, only females and only males), there was a good fit to the actual weight, although the R^2 for males was slightly lower than for females, the R^2 for males is still a very high and satisfactory value.

The experiment showed that males had a greater dispersion in weights, particularly when exceeding 30kg. This is supported by the fact that the predicted weights did not overlap with the observed weights as precisely as for females (see Figures 16C and 16E). Additionally, at the end of the six-week experiment, males weighed more than females, as shown in Figures 16E and 16F. Out of the images used for training, only 5.9% of the males reached weights greater than 30 kg, while only 1.6% of the females reached this value.

However, the dataset for both males and females were focused on weights between 8 and 30kg. The model was trained using many pigs within this range, while those weighing over 30kg were a minority of the total images. In case 3, where only males are considered, the coefficient of determination is lower than that of females. This is due to a higher percentage of pigs weighing more than 30kg, which the model was not trained to analyze as it mostly dealt with pigs weighing less than 30kg.

Despite the lower coefficient of determination for males compared to females, the model still accurately predicts weight. Most training images fall within the 8kg to 30kg range, with a minority above 30kg. However, this did not affect the coefficient of determination when combining males and females, resulting in a value of 0.98 (Figure 16A).

Figures 16 B, 16 D and 16 F show the density of the predictions with respect to the actual weights. For the first case of analysis (males and females together), the highest density of animals is around 10 kg, with an estimated and observed average of 16.79 kg and 16.84 kg, respectively, which means that the difference between the actual and predicted average weight is 0.05 kilograms or 50 grams.

For the second case (females only), it is evident that the highest density weights are close to 10 kg, with predicted and observed averages of 14.28 kg and 14.21 kg, respectively. In this case, it is noteworthy that the highest concentration of weights is found from 8 kg to approximately 25 kg, with a difference of 0.07 kilograms or 70 grams between the means.

For the third case (males only), it is evident that the points on the weight adjustment are more dispersed compared to the females (Figure 16 E) and the highest weight density is around 15 kg. The average estimated and observed weights are 19.96 kg and 19.71 kg respectively, a difference of 0.25 kilograms or 250 grams. It is evident that the absolute difference between estimated and observed weights is smaller when males and females are analyzed together. With these comparisons, the development of the model allowed to identify that although the females had a better R^2 fit than the males, it was the males that achieved the greatest weight gain at the end of the experiment, exceeding 35 kg.

According to Table 3, The architecture defined with the custom network has an input layer where it takes an RGB image (red, green, blue), three bands, transforms this image into a 32-band image and then 128, 64 and 32. The Conv2D layer is the convolution part where it learns to extract the characteristics of the images and then comes the Flatten layer where it transforms the last layer of images into a one-dimensional array to be the input layer of the artificial network of dense layers for classification, with the ReLU activation function, used to compute the hidden layer values (Goodfellow et al., 2016). The last layer has an output that is the weight, a numerical variable, so the size is 1.

4. DISCUSSION

In this method, all images could be processed without removing parts of body, identifying each complete animal body from the top view without affecting accuracy or metrics such as MAE and Loss, in comparison to (Kongsro, 2014; Y. Wang et al., 2008), in which study were removed head, ears, and tail from pig images to improve accuracy in live weight estimation.

(Kashiha et al., 2014) automatically estimated weight from pigs using machine learning techniques (ellipse fitting algorithm and area calculations) of pigs from 23-45 kg, controlling illumination conditions. They reached 97.5% of accuracy (error of 0.82 kg) when the group of fattening pigs were analyzed and 96.2% individually (error of 1.23 kg). However, fattening pigs are isolated from others, which allows a less demanding weight prediction of each animal. In the weaning phase, due to their adaptation to the environment, the animals are in agglomerations to mitigate the effects of the microenvironmental conditions of the facility and. Therefore, predict weight in early stages of production is decisive in achieving the final weight for marketing in finisher pigs, depending on management mainly in the first week after weaning, as mentioned by (Pluske et al., 2003; Tokach et al., 1992).

In this case, it was proposed a combined analysis of males and females and separating by gender as suggested by the authors (Kashiha et al., 2014) at the end of their study. In this research, all cases (males and females together, only females and only males), reached R^2 higher than 0.96, although females were concentrated more under 30 kg and males obtained a higher performance in weight gain getting slightly more than 40 kg, as Figure 16 shown. The accuracy for females and males was 99.7% (absolute error of 0.05 kg), for females was 99.6% (absolute error of 0.07 kg) and for males was 98.24% (0.25 kg), higher values of accuracy mentioned by (Kashiha et al., 2014).

The results of pigs weaning behavior were compared with (H. Chen et al., 2023). The authors gathered weight information of males and females applying a Radial Basis function in pigs with 150-190 days-age and weight of males (boars) was generally higher than females (sows), but the distribution of boars was more dispersed than sows. In this research, males reached the same behavior of authors, a greater dispersion than females' weights, considering the study stages of the authors and ours were different. They obtained a lower coefficient of determination of 0.63 in weight prediction using the Multilayer RBF network, than this study where a R^2 above of 0.96 for all cases, was obtained. It could be due to authors using five one-dimensional parameters (body length, height, chest circumference, abdomen, and waist circumference) as input of the network, which makes an exact and time-demanding measurement difficult in each animal.

Comparing the study with the one elaborated by the authors (Jun et al., 2018; Y. Wang et al., 2008), they obtained similar coefficients of determination, with more challenging production conditions. They used image analysis methods to segment one animal at a time and obtained errors of 3.15 kg due to failures in the binarization process in the images due to their non-straight postures of pigs during image capture, resulting in a model with R^2 of 0.72 and 0.99 respectively. They used machine learning strategies by feeding postural characteristics of the animals into a neural network (Jun et al., 2018), but had several drawbacks in the contrast of images and adjustment of postures for subsequent weight prediction. In the study developed by (Y. Wang et al., 2008), they removed body parts to increase the accuracy of prediction weights. In this sense, even when analyzing individual pigs, it is evident that, although detecting and predicting the weight of each animal separately and under controlled conditions is generally less demanding in terms of time and resources than analyzing groups of pigs under normal production conditions, this is not a guarantee of high precision, as was the case of (Jun et al., 2018). Hence, machine learning strategies show a great performance when analyses are conditioned to specific parameters (posture, lighting, group-housed or non-group-housed), this makes it less feasible to apply these kinds of strategies to real productions.

Comparing MAE with an alternative to weight prediction as use of 3D cameras, (Ositanwosu et al., 2023), obtained a MAE of 4.44 and 4.47 for two models assessed, using data-images of four years (2016-2020) from Duroc fattening pigs using three 3D cameras Kinects to capture point clouds and measured the body characteristics (body length, height, width, waist, and others). They were able to use data augmentation techniques to make the methodology less time-consuming and use strategies such as correlations between the real weight and the 3D model, as applied in this study, without having to measure specific body characteristics. Although 2D images were used here, a better accuracy was obtained than that studied by the authors, using strategies such as Data augmentation to avoid long processing times. Our methodology obtained a maximum MAE of 0.25 kg when only males-images were analyzed.

By other hand, (G. J. Tu & Jørgensen, 2023) estimated weight of pigs in slaughter pens by determining width and length and ratio of these measurements to identify if animals were standing. They used a segmentation algorithm to calculate area and allometric relationship to prediction function with a high accuracy in weight prediction (97.76%). However, they had a major proportion of discarded images due to posture in the identification phase, finding only about 10% of all frames segmented of standing pigs, which is evident the planning process at segmentation phase was inefficient. Their high accuracy was obtained thanks to controlling a standing position and measuring body features in the smaller pigs because all pigs were recorded at the same time in a high range of pig's size (20 to 105 kg), which caused the bigger pigs did not fit in camera range. This is why the focus of our research was concentrated only on a specific and decisive phase of production.

In comparison with the authors, it is evident that the planning phase is important to avoid inefficient processing. For this reason, the objective of weight predicting needs of having to take into account initial parameters such as, productive stage and weight range of each treatment, as considered in this study, in addition to the general experimental setup (camera range, pens, lighting, number of animals per pen, etc).

On the other hand, this study had a significant impact on frame processing time in addition to the accuracy obtained. It was important to make an initial comparison of architectures and optimizers to choose the best performance and lowest time of processing. The selection of the DenseNet121 architecture and Adam optimizer was evidence that the time of 9.02 seconds to process 2714 images in their respective stages of training and test was better than the time employed by (Kawasue et al., 2023), where they spent about 3-4 seconds per pig and (Cang et al., 2019), spent 0.174 seconds per images in test stage, which represents about 7.9 minutes for analyzing 2729 images in the test dataset.

Comparing Mean Absolute Error with obtained by (Cang et al., 2019) who proposed a Region Proposal Network based into the Faster R-CNN and Adam optimizer, using depth images. The weight range of sows was from 159.27 kg to 167.27 kg and obtained a high performance with a MAE of 0.644 kg. However, the authors suggested that the method can be used to group housed pigs' live weight estimation and ensure that different posture of pigs could affect the weight accuracy. Likewise, an appropriate position and stationary body conditions are important parameters to detect live weight in ideal scenarios. However, in real productions, controlling animal behavior to collect data can be time consuming. Proof of this is time consuming in their method.

The results obtained compared with authors (Kawasue et al., 2023), they used depth cameras and AR glasses (Augmented Reality) to predict the weight of a group of pigs close to the time of shipment with a machine learning method. However, their study's accuracy was influenced by the number of training data and their prediction's errors oscillated between 2 kg and about 12 kg. Even though they used Yolov5 for detection and principal component analysis to correct orientation on the ground, the estimated overall shape of each pig from the spine curve is conditioned by their position near the center of the screen. This process naturally takes more time than estimating the weight of several animals at the same time.

Thus, among all deep and machine learning methods compared, it is evident that high errors can be obtained depending on the image's selection, training, and validation model. As a result, the model used in this research allowed the development of new strategies for monitoring and future applications classifying animals by weight under real production conditions. It is also important to emphasize that the adjustments made in the three cases are the results of images taken at different times of day, with different positions of the animals and in situations of agglomeration, which generated a more general prediction system.

The method used was a non-invasive method, beyond the marks on the back of the animals and the manual weighing of the animals to calibrate the weight prediction model. At the level of large productions, marking each animal becomes infeasible. Therefore, an alternative to not marking each animal can be to couple the detection model with a tracker model to follow the trajectories of each pig in the pen as studied by (Zhang et al., 2019).

Summarizing, the experiments carried out by (Jun et al., 2018; Kashiha et al., 2014; Kawasue et al., 2023; G. J. Tu & Jørgensen, 2023), all authors applied different machine learning methodologies to obtain higher errors than this study and their weight prediction systems needed controlled conditions to be highly accurate. In this sense, it is an evident reason that deep learning can maintain lower errors in weight prediction, without depending on conditions such as illumination or position of the animals as evidenced in our results.

In the phase of identifying the number of pigs in the cropped images, there was an initial limitation when they were lying down or joined together. In this phase, it was important to associate the image with a clear coding that allowed to associate the image with the video taken on the corresponding day and time. Thus, it was possible to identify the pig due to the tracking of the movements collected in the videos, which makes the model used in this study more general. For this reason, future work could include in this method a system of tracking animals, which, in addition to identifying each individual without losing information, would help to detect other variables as animal behaviors.

Finally, the method used in this research had a great performance in challenging conditions. The main objective was to develop a weight prediction system for pigs in weaning phase from 8 kg to about

32 kg, housed in groups and by ensuring their natural behavior in pig's husbandry, guaranteeing a high accuracy, and proposing a suitable method to be used in an app for more access of producers.

5. CONCLUSIONS

One of the improvements that could be made to the model is to try to detect each animal without any kind of mark or tag on the ears, so that it is totally free of human intrusion and totally applicable to large pig productions.

A comparison of architectures allowed one to choose the most viable model using metrics such as time, validation error and training.

With the methodology used, is it possible to create an application that allows the producer to monitor in real time the weight of each of the animals without the need to analyze each individual. It is enough to upload the video of the animals and the application executes the detection of each individual and, in turn, estimates the weight. This is a great advance in terms of reducing time and resources for weighing the animals, in addition to allowing its application in medium and high production systems.

A weight estimation by means of Deep learning techniques allowed to fulfill the objective of estimating the weight of the animals in a more direct way and without conditioning the analysis to variables such as position of the pigs or whether they are in groups or not.

The idea developed in the present study can be applied to other types of livestock production that need weight predictions, such as broiler or beef cattle production, although it should be clarified that differences between breeds need to be considered. In this case, it is necessary to adjust again the initial detection characteristics of each individual, so that the program recognizes the body dimensions of each animal species.

Although in the present study an attempt was made to create a neural network (CustomNet) to predict the weight of pigs, much more validation and testing is needed for it to have the same accuracy as networks that are already trained in many AI scenarios.

With the approach of the present study, it is possible to establish categories in which a future model can classify animals that are in weight ranges suitable for shipment and those that are still in the weight gain phase, it means a growth curves monitoring.

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7. OVERALL CONCLUSION

Most studies on predicting pig weight using artificial intelligence focus on growth and finishing stages and control the position and number of animals used.

There is insufficient information regarding weight detection methods during the early stages of pig production, specifically during weaning. Additionally, Deep Learning methods should be linked with graphical interfaces to provide producers with clear and prompt updates on the weight of each animal.

This study serves as a reference point for future applications of Deep Learning tools in weight prediction during early stages of pig production under real production conditions.

To maintain productive performance of piglets after separation from lactation, it is important to consider various factors. The tools presented here, along with future studies on diseases and behavior, can help track growth and identify variables that may affect performance. This will enable timely and appropriate decision-making for more efficient management.

8. Supplemental material S1

Table 3. Customer Network architecture.

Layer	Number of filters / Neurons	Filter size / Activation Function
Input	-	Variable size
Layer Conv2D #1	32	(3, 3) / ReLU
Layer Conv2D #2	128	(3, 3) / ReLU
Layer Conv2D #3	64	(3, 3) / ReLU
Layer Conv2D #4	32	(3, 3) / ReLU
Layer MaxPooling2D	-	(2, 2)
Layer Flatten	-	-
Layer Dense #1	64	ReLU
Layer Dense #2	32	ReLU
Output Layer	1	Linear (Regression)