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Free usable space estimation in broiler farms using an image segmentation algorithm

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ABSTRACT
Free usable space in broiler farms has a substantial impact on the welfare and health of the chickens. In this paper we use a computer vision algorithm to estimate free usable space in this kind of farms. This method uses a real-time camera that collects images from the farms and an image processing algorithm based on a U-Net architecture, which estimates the free usable space available. The results of the method are compared with manual labels, and it is shown that the method is accurate and efficient in estimating the free usable space.

Section: RESEARCH PAPER

Keywords: segmentation; broiler; u-net; deep learning; computer vision; animal welfare; free usable space; stocking density

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1. INTRODUCTION

Broiler farming is an important activity in modern agricultural production. Chicken meat is one of the main sources of protein in the human diet, and the broiler industry is one of the largest in the world in terms of production and consumption [1].In addition to its relevance in food production, broiler farming also has a positive impact on the economy and the environment. The broiler industry is a generator of employment and contributes to the economic development of many regions. Moreover, the production of chicken meat is more efficient in terms of resources than the production of meat from other animals, which makes it a more environmentally sustainable option [2].

However, broiler farming also presents challenges and concerns, such as diseases control or maximizing the feed conversion ratio. One of the biggest challenges is ensuring the welfare of animals on the farms. Confining animals in limited spaces can cause health and behavioral problems, and it is important to take steps to improve their quality of life.

When animals do not have enough space to move around and do their natural activities, they can develop physical and mental problems [3]. For example, chickens can suffer leg and wing deformities due to a lack of space to move and exercise [4]. In addition, when herds do not have enough space to grow and develop, they can also be more prone to diseases [5]. This also can affect the quality and performance of herds, reducing production [6]. It is also believed that having a significant inter-individual distance has a positive impact on animal welfare, as in [7] and [8]. For this reason, efficient farm space management is a major challenge in modern broiler production [9] to get sufficient economic return from the house to make it economically sustainable and is also crucial for the health and well-being of the animals.

In the context of broiler farms, “free usable space” refers to the amount of space available for the birds to move around and engage in natural behaviours. This is slightly different from other measures of space utilization on a farm, such as stocking density, which refers to the number of animals per unit of area.

Stocking density is typically measured in terms of weight, such as kilograms per square meter, or in terms of the number of animals per square meter. It is a useful measure for comparing the density of different farms or for determining the maximum number of animals that can be raised in each space. However, it does not consider the size and weight of the individual animals, or their ability to move around and engage in natural behaviours.

In contrast, free usable space is a measure of the amount of space available for the animals to move around and engage in natural behaviours. It considers not only the density of the animals, but also their size and weight, as well as the local distribution of the animals within the farm. This makes it a more accurate measure of the animals' welfare and their ability to engage in natural behaviours.

The amount of free usable space is a function of two factors: the local distribution of the birds, and the weight and volume of the birds.

The local distribution of the birds refers to the spatial arrangement of the birds within the farm. In a well-designed farm, the birds should be distributed evenly throughout the space, with enough room for each bird to move around and access food, water, and other resources.

The weight and volume of the birds is also an important factor in determining the amount of free space needed. As the birds grow and gain weight, they require more space to move around and engage in natural behaviours. This is because heavier birds have a larger volume, which means they take up more space in the farm.

The development of accurate and efficient methods to estimate free usable space on farms is a major step to improve the production and ensure the sustainability of the sector. Until now, the only way to estimate useful free space on farms has been through manual measurements. However, these methods can be laborious, expensive, and inaccurate.

Computer vision technology has allowed the development of more efficient methods to automate counting chickens on the farm [10].

In this paper we want to present a new method for estimating percentage of free usable space in the farms. Our approach uses image processing techniques to analyse the images. This information can be useful for farmers who want to maximize the use of space on their facilities and increase the efficiency of their production. Furthermore, this method is much more accurate than manual chicken counting.

The paper is organized as follows:

- Algorithms and Methods: This section describes in detail the method used to estimate the amount of free usable space in a chicken farm from images captured from the top of the facility.
- Experimental results: this section presents the results obtained by applying the method to a set of images of real chicken farms.
- Conclusions and future lines of work: this section summarizes the main conclusions of the article and proposes future lines of work to further improve the precision and efficiency of the computer vision method to estimate the amount of free usable space in chicken farms and extract useful information from the data generated by our algorithm.

2. ALGORITHMS AND METHODS

In this section we explain the algorithms and methods used to estimate the free usable space. For this we have used an image semantic segmentation approach [11].

Semantic image segmentation is an image processing technique that aims to divide an image into different regions or segments and assign each of those regions a semantic label that describes its content. For example, in an image of a street with buildings, trees, and people, semantic segmentation could divide the image into different segments corresponding to each of those elements, and assign labels such as "building", "tree" and "person." This approach has been used successfully in many applications such as medical images [12] or autonomous driving [13].

There are different semantic segmentation algorithms that can be used to divide an image into different regions. The classic approaches, use a set of predefined rules to divide the image into segments and assign labels to them [14].

For instance, a rule may stipulate that entities sharing similar characteristics with a predefined criterion are to be collectively categorized under a specific label. This procedure can encompass techniques such as thresholding algorithms, which involve establishing a threshold for certain attributes, and then classifying all entities that fall beneath this threshold into a designated category. Additionally, methodologies like region growing algorithms [15], [16] initiate with a seed entity, subsequently incorporating adjacent entities into the collective group based on predetermined similarity criteria, which could include attributes like intensity values or spatial distances between entities. We also have algorithms based in rules that it uses edge detection techniques ([16] and [17]) to divide the image into different segments and then use object classification techniques to do so.

On the other hand, we have algorithms based on deep learning [18] and [19], which use machine learning techniques based on deep neural networks to learn how to segment images and assign labels. To do this, we need to train them with a set of previously labelled images, and then they use what they have learned to segment new images and assign labels to them. One of the best-known deep learning-based algorithms for image segmentation is U-Net [20], which has been widely used in the medical field to detect tumours in MRIs. U-Net uses an autoencoder neural network architecture that combines high and low-resolution information for accurate image segmentation. Another algorithm based on deep learning is Mask R-CNN, which is another extremely popular method used for image segmentation in real time. Mask R-CNN [21], uses a convolutional neural network that can detect objects in an image and generates an accurate mask around each detected object. This mask can be used to segment the objects in the image and exclude the background.

In general, deep learning is better than rule-based approaches for image segmentation due to its ability to learn automatically from a large data set and its ability to adapt to different situations, for instance, not all pixels of a colour like "grass" belong to "trees". This allows the model to be more accurate and generalizable in its image segmentation task. However, they usually require large manually labelled data sets to be trained.

In our work we have decided to use a U-Net type architecture because it presents a particularly good balance between accuracy and computational cost.

The U-Net is an architecture with an "encrypt" branch that contracts as you move through the network and a "decode" branch that expands as you move through the network to the output layer. In the coding branch, layers are stacked, and images are down-sampled as you move through the network, allowing the network to learn more abstract features as finer details are clumped together. In the decoding branch, the layers are unrolled, and the resolution of the images is increased again, allowing the network to combine these abstract features with the finer details to produce accurate segmentation of the image.

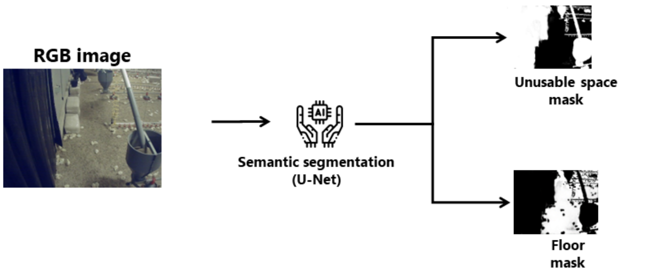

Figure 1. Scheme representing the two output masks of our model given an RGB image.

To train a U-Net, labelled images are needed, that is, images that have already been classified, usually by a human expert, and have a binary mask associated with each one. A binary mask is an image that contains only two values: 0 and 1. Pixels with a value of 0 represent the background of the image, while pixels with a value of 1 represent the object of interest.

We have trained our model to be able to segment the image into two different masks or regions of interest. One region belongs to the farm floor, and another belongs to the space that cannot be used because it belongs to walls, pipes of drinkers or feeders or other kinds of objects that chickens cannot reach as we show in Figure 1.

Once the two segmentation masks have been detected, what we do is count the total number of pixels in the mask belonging to the farm floor and the number of inaccessible pixels. And applying a simple formula that subtracts from the total number of pixels in the image the pixels that are not accessible, we calculate the percentage of pixels that belong to the ground, that is, the pixels percentage that belongs to the free usable space as we show in the following equation:

$$\%\, FreeSpace = \frac{\#FloorPixels}{\#TotalPixels - \#UnusablePixels} \times 100\,. \quad (1)$$

3. EXPERIMENTAL RESULTS

In this section we show the experimental setup that we have used to test our model as well as the performance results that we have obtained in different scenarios. We also show charts of the evolution of the free usable space obtained throughout the cycle using our algorithm in different farms.

Thus, to carry out experiments we have considered the following points:

- We have used images of 6 different farms with cameras installed on top of the farm (from when the youngest chickens enter to the farm until they are ready to be taken to the slaughterhouse). This allows us to obtain a large number of images with different conditions and situations, which helps us to evaluate the generalizability of the model. Also, by using images from different farms, we can ensure that the model is not biased towards just one farm.
- We have manually labelled 466 images to train and 218 to test the model. By using a separate dataset to test the model, we can evaluate its performance on data that was not used to train it avoiding the overfitting problem.
- The metric used to evaluate the model has been the Intersection Over Union (IoU). The IoU is a measure of similarity between two data sets and is calculated as the intersection between the two sets divided by their union. In our case, it is calculated as the intersection between the pixels labelled by the model and the pixels labelled by a human expert, divided by the union of both sets of pixels. This metric allows us to evaluate the accuracy of the model in identifying free usable space in the images. Values close to one mean better accuracy.

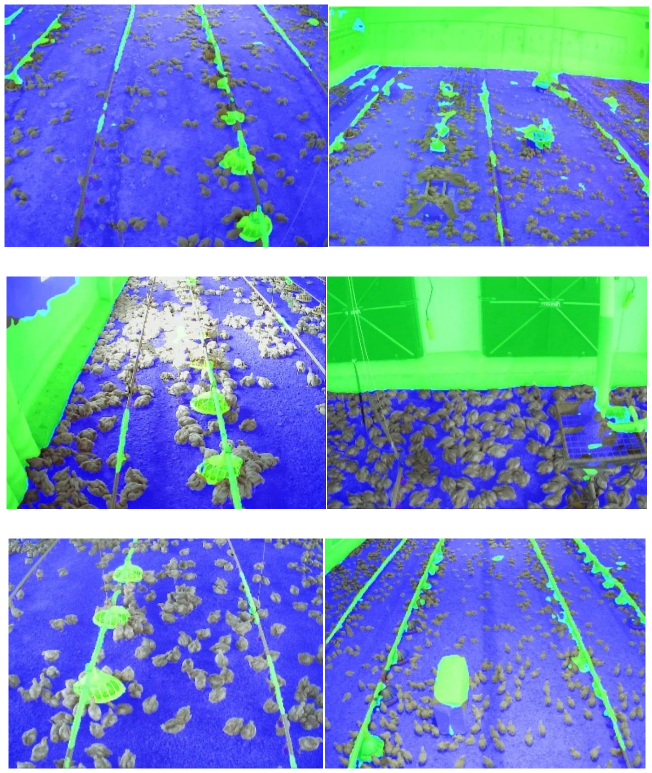

Figure 2. Examples of the predicted segmentation masks. Blue: floor, green: unusable space.

Figure 2 shows some example images with the result of the segmentation algorithm.

The images show the results of the segmentation masks, we can see that the performance of the model is quite good identifying the pixels of the ground and those of other elements in the farms, such as walls or machinery. However, it is not able to detect very well drinkers, feeders, and pipes when they are too far away.

As discussed in the previous section, the U-Net architecture is based on an encoder-decoder, in which the encoder is used to reduce the dimensionality of the input image and extract relevant features, while the decoder is used to reconstruct the original image from these features. However, in some cases, the encoder can lose valuable information by reducing the dimensionality of the image, which can affect the accuracy of segmentation of the smallest elements in the image. This is because the further away these elements are from the image, the more difficult it is for the model to identify and segment them correctly. Therefore, the U-Net architecture may have difficulty correctly segmenting smaller elements in the image.

In any case, the total percentage of pixels in the pipes is not truly relevant when calculating the total percentage of free usable space pixels and the results are still particularly good despite this, since ground and walls are, in general, correctly detected.

Table 1 shows the percentage of pixels that are within the IoU in relation to the dataset that has been manually labelled in the set of test images for each farm. The results show that the average percentage of pixels within the IoU (fourth column) is around 90 %, which indicates a good precision of the model in the segmentation of the images.

Table 1. Percentage of IoU pixels in each of the farms and every mask.

Farm	IoU		
	Floor	Unusable Space	Average
Farm 1	0.84	0.88	0.86
Farm 2	0.82	0.85	0.83
Farm 3	0.87	0.96	0.92
Farm 4	0.89	0.96	0.93
Farm 5	0.89	0.95	0.92
Farm 6	0.87	0.91	0.89
Average	0.87	0.93	0.90

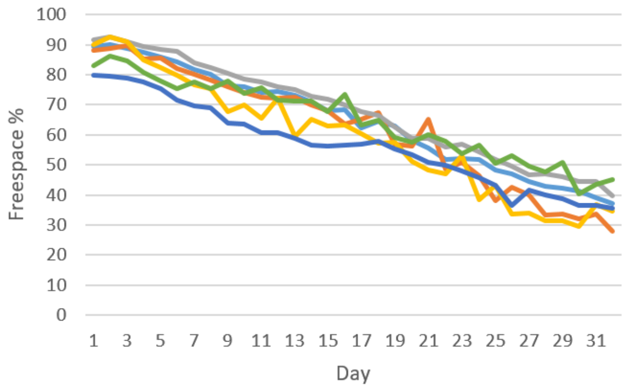

Figure 3. Free usable space percentage versus day of production cycle.

Finally, in Figure 3, we show the evolution of the free usable space during the first 32 days in six different production cycles. A camera located on the top of the farm was taking a picture every minute. The moments in which the light intensity was too low were discarded, and finally the mean free usable space was calculated using our algorithm. In some cases, the curves are not completely smooth, this may be because sometimes the chickens are unevenly distributed throughout the farm and there may be a larger group of chickens in front of the camera. However, the general trend in the evolution of free usable space is consistent with our observations and the growth rate of chickens.

4. CONCLUSIONS AND FUTURE WORK

The amount of free usable space in a broiler farm is an essential factor that needs to be carefully managed. To achieve this, we have presented a computer vision algorithm in this paper that is designed to estimate the amount of free usable space in an automated way. The algorithm is based on a U-Net architecture, which semantically segments image pixels by classifying each pixel according to its class. This automated process offers significant benefits over manual inspection, including better measurement accuracy and real-time data.

The algorithm has been tested, and the results show that it is highly accurate, with an average Intersection over Union (IoU) around 90 %. The observations have also remained consistent throughout the entire production cycle, providing valuable insights into how the free usable space changes over time.

While the algorithm has shown great promise, it still has some limitations. For instance, the model may have difficulty segmenting small objects such as feeder pipes and drinkers, which could impact its accuracy. To address this issue, the model's size can be increased by adding more convolutional layers to process higher resolution images with greater detail. However, this could lead to increased computational costs.

In the future, the data generated by this algorithm can be used to conduct further studies. For instance, the relationship between the free usable space and the productive performance of the farm, such as the amount of feed consumed, and the amount of product obtained, can be analysed. Additionally, the algorithm can also be used to estimate the size of the animals and compare it with the expected size at each stage of the production cycle to ensure that the animals are progressing properly. This would enable size thresholds to be established, and this information could be used to identify and correct potential problems such as inadequate feeding or animal diseases.

In addition to the potential uses mentioned above, it would also be interesting to conduct a comparative study of different image segmentation algorithms. Although the U-Net architecture has shown promising results in estimating the amount of free usable space, it would be worthwhile to investigate how other algorithms perform in terms of both computational cost and accuracy. This would allow for a better understanding of the strengths and weaknesses of different algorithms and could lead to the development of more efficient and accurate models in the future. Such studies could be useful for other applications of computer vision as well, where different segmentation algorithms could be compared to identify the best performing one.

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