Determination of the Live Weight of Farm Animals

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In cattle breeding, regularly taking the animals to the scale and recording their weight is important for both the performance of the enterprise and the health of the animals. This process, which must be carried out in businesses, is a difficult task. Due to the drawbacks of direct measurement approaches, a variety of indirect measurement approaches have been proposed.

animal weight estimation deep learning image processing semantic segmentation stereo vision

1. Introduction

Livestock farming has become an important industrial sector as well as a side occupation for people engaged in agriculture in rural areas. Thanks to practices such as cooperatives, producer unions, registered breeding, artificial insemination practices, and livestock supports, the place of the livestock sector in the country's economy has started to gain more importance. It is necessary to determine the weight of the animals raised in cattle breeding farms and to follow them regularly. Increasing the profitability of the business depends on the regular follow-up of live weight [1].

The most common method of measuring the live weight of farm animals is traditional measurement using a scale. Although this direct approach is very accurate, it comes with various difficulties and limitations. Firstly, animals are required to be moved to the site of measurement scale, which can be time-consuming and laborious, especially in farms with a large number of animals. Secondly, this whole operation with the separation of animals from their natural environment causes stress, and therefore negatively affects their health and milk yield. Due to the drawbacks of direct measurement approaches, a variety of indirect measurement approaches have been proposed in the literature [2]. In indirect measurement, the true value of animal live weight is estimated by a regression model trained on various features extracted from measurements obtained from several sensors such as 2D [3] and 3D cameras [4], thermal cameras [5], and ultrasonic sensors [6].

2. Livestock Weight Estimation Methods

There are several studies in the literature that are based on image processing techniques on 2D images. In a study by Weber et al., the live body weight of cattle was estimated using dorsal area images taken from above using a kind of fence system [7]. Their system first performs segmentation and then generates a convex hull around the segmented area to obtain features to feed a Random Forest-based regression model. Tasdemir and Ozkan performed a study where they predicted the live weight of cows using an ANN-based regression model [8]. They determined various body dimensions such as wither height, hip height, body length, and hip width applying photogrammetric techniques on images of cows captured from various angles. Wang et al. developed an image processing-based system to estimate the body weight of pigs [9]. Their main approach was to process images captured from above to extract features such as area, convex area, perimeter, and so on. Then, using these features, they trained an ANN-based regression model for weight prediction. A Fuzzy Rule-Based System was also utilized in cattle weight estimation by Anifah and Haryanto [10]. They obtained 2D side images of cattle from a very close distance of 1.5 m. After applying the Gabor filter to the images, they obtained body length and circumference as features. Finally, they designed a fuzzy logic system to estimate body weight.

Three-dimensional imaging techniques also found application in body weight estimation systems. Hansen et al. used a 3D Kinect-like depth camera to obtain the views of cows from above as they passed along a fence [11]. Applying thresholding, they obtained the segmented area of cows to reach a body weight estimate. In another study where a 3D Kinect camera was used, Fernandes et al. processed images taken from above of pigs by applying two segmentation steps [12]. Then, they extracted features from segmented images such as body area, volume, width, and height to feed a linear regression model to obtain the weight estimate. In a similar study, Cominotte et al. developed a system to capture images of cattle using a 3D Kinect camera [13]. They trained and compared a number of linear and non-linear regression models by feeding them with features extracted from segmented images. In a study by Martins et al., a 3D Kinect camera was used to capture images of cows from lateral and dorsal perspectives [14]. They used several measurements obtained from these images to run a Lasso regression model to estimate body weight. Nir et al. used a 3D Kinect camera as well to take images of dairy heifers to estimate height and body mass [15]. Their approach was to fit an ellipse to the body image to calculate some features. Then, they used these features to train various linear regression models. Song et al. created a system to estimate the body weight of cows using a 3D camera system [16]. Similar to previous studies, they extracted morphological features from 3D images such as hip height, hip width, and rump length. Combining these features with some other cow data such as days in milk, age, and parity, they trained multiple linear regression models. Another study that employed a 3D Kinect camera is the one conducted by Pezzuolo et al. [17]. They captured body images of pigs using two cameras from top and side, and then extracted body dimensions from images such as heart girth, length, and height using image processing techniques. They developed linear and non-linear regression models based on these dimensions to predict weight.

Advanced scanning devices were also introduced in body weight estimation studies. Le Cozler et al. used a 3D full-body scanning device to obtain very detailed body images of cows [18]. Then, they computed body measures from these 3D images such as volume, area, and other morphological traits. Using these measures, they trained and compared several regression models. Stajnko et al. developed a system to make use of thermal camera images of cows to extract body features and then used them in several linear regression models to estimate body weight [19].

Stereo vision techniques are also used in the determination of live animal weight. Shi et al. developed a regression model to analyze and estimate the body size and live weight of farm pigs under indoor conditions in a farm [20]. Their system was based on a binocular stereo vision system and a special fence system through which animals passed for taking the measurements. They segmented the images obtained from the stereo system using a depth threshold and predicted the body length and withers height, then the body weight. Some other notable studies using stereo vision are by Nishide et al. and Yamashita et al. [21][22].

Deep learning-based approaches are very popular today due to their success in image-processing applications. Deep learning is a special form of neural network algorithm. Although it has achieved the most advanced results in many fields, its use in determining the weight of livestock is limited [23]. There are studies that apply deep learning algorithms and determine the weight of pigs [24][25].

When examining the prior research on the estimation of live body weight of farm animals such as pigs, cattle, cows, and heifers, there is a common approach to capturing images of animals that the animals are forced to move into special types of boxes or fences, or they are forced to pass through a special passage. This operation is very similar to traditional weight measurement with scales, and therefore, it also requires the separation of animals from their natural environment, and it causes stress-related problems in their health and milk yield [3].

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