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Early Detection of Lameness in Cattle with Image Processing Techniques

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Abstract: Lameness in dairy cattle has a negative effect on fertility, milk yield and various behaviors. Therefore, lameness in cattle causes significant economic losses in countries. In our article, it is aimed to detect lameness in cattle early with image processing techniques. Deep learning and image processing techniques were used in the article. In the article, YOLOv5 algorithm is used for object detection and Shufflenetv2k30 algorithm is used as image processing technology. Within the scope of the article, the images were subjected to a preprocessing (data augmentation) and then the cattle in the selected photos were identified by our trained deep learning model. The detected cattle were tagged and then the posture estimation of these tagged cattle was made. The angles between the joints of the cattle were found on the cattle whose posture pose was estimated. In the performance analysis, training was started with the weights of the Pre-training yolov5l model and the best weight output of the 200 epoch trained model was 75%. The best weight output of the model trained from zero to 400 epochs without using any model weights was 63%. Pre-training was started with the weights of the shufflenetv2k30 model and the weight output of the model trained for 400 epochs was 71%. This article will contribute to the studies to be done in the academic field and will create important data for the studies to be done in the livestock sector.

Keywords: Image Processing, Deep Learning, Cattle Detection, Lameness Detection

1. INTRODUCTION

Foot diseases have emerged as a leading cause of economic losses in modern cattle breeding countries, ranking among the top three health-related concerns leading to culling. (NAHMS, 1996; Enting et al;, 1997; Kossaibati and Esslemont, 1997; Atkins and Shannon, 2002). With the spread of modern dairy cattle, the proportion of cattle suffering from foot diseases has increased (Clarkson et al., 1996). For example, it has been reported that the rate (incidence) of cattle with foot diseases in England was 4% in 1957/58, 25% in the early 1980s and 54.6% in the 1990s (Leech et al., 1960; Whitaker et al., 1983; Clarkson et al., 1996). There are studies on the prevalence of lameness in Turkey. According to the results of some studies, Belge et al., (2005) reported that the rate of lameness in dairy cattle varies between 13% and 58%, Yaylak et al. (2007) also found that the prevalence level of lameness was 28.2% on average in the study they conducted in 21 enterprises in İzmir. The common indicator of foot diseases is lameness ranging from mild to severe (Görgül, 2004). Lameness is an important factor affecting animal welfare and reducing profitability (Boelling and Pollott, 1998). Economic losses from foot diseases are much higher than treatment costs.(Stokka et al., 1997). For example, in the UK, a case of lameness costs £33.8 for the treatment (medicine and veterinarian), while the total cost of a case of lameness is £246.2 (Kossaibati and Esslemont, 1997). No study has been found on this subject in our country. However, an expenditure of 40-60 YTL is made for the treatment of a lame cow (Vet. Ahmet Gevrek, private interview). Economic losses due to foot diseases are due to the cost of treatment, the need for additional labor, the milk wasted during the treatment, the decrease in milk yield, the increase in the risk of weeding, the prolongation of the calving interval, the additional insemination costs and the increase in other diseases. (Kossaibati and Esslemont, 1997; Stokka et al., 1997; Enting et al., 1997). Although lameness causes great economic losses, breeders often underestimate the prevalence and severity of lameness.

2. LAMENESS IN CATTLE

There are many causes of foot diseases. Among these reasons, leg structure disorder, hereditary factors, increasing age of the cow, cattle breeding started to be done in a closed and semi-closed system in more modern barns and cows are not taken to pasture, generally kept on concrete floors, nails are constantly exposed to abrasive conditions, high milk yield and body weight, high energy rations, silage-weighted feeding, keeping the feet in contact with fouled barn environment, and being in contact with foul dry matter (KM) can be counted as factors. et al., 1992; Boelling and Pollott, 1998; Görgül, 2004; Atkins and Shannon, 2002; Leach et al., 2005).

Objective and subjective methods are used to detect lameness. The basis of the objective method, which has been used in humans and horses before, and recently in cattle, is based on measuring the physical characteristics of animals' walking and expressing them in units such as meters, seconds and kilograms (Sedlbauer, 2005). Objective methods make use of biomechanical techniques. Biomechanics is a science that studies biological systems using mechanical engineering methods. This branch of science makes use of kinematics (science of motion), force platform (the instrument used to evaluate the state of balance), electromyography (the instrument that measures the electrical currents produced by a moving muscle) and accelerometer (speedometer) in the detection of lame cows (Flower et al., 2005). In addition, cow activity collars and pedometers, which measure the activity of cows, can also be used to detect lameness. The other method used to detect lameness is the subjective (indirect) method. Although there are different scoring systems (methods), it is called the lameness scoring system. Lameness scores vary according to the presence of movements thought to be related to lameness and the severity (level) of lameness. Lameness scores can be discrete (Manson and Leaver, 1988; Sprecher et al., 1997) or continuous (Flower and Weary, 2006). Movements thought to be associated with lameness in dairy cows collectively Nordlung et al. (2004) reported. These movements are that the cow shakes its head when the problematic foot touches the ground, the back of the animal is humped due to pain, drooling from the mouth in case of severe discomfort, shortening of the stride length, trying to step on the unaffected side of the sole of the foot so that it can carry its weight, decreased walking speed and stopping frequently to rest the aching foot while walking.

Using different combinations of these movements, different lameness scoring systems have been developed for dairy cattle. There are important implementation differences between scoring systems. However, there are two main methods developed by researchers from England (Manson and Leaver, 1988) and the other from the USA

(Sprecher et al., 1997) for scoring foot glitches (Robinson and Juarez, 2003). According to the method developed by Manson and Leaver (1988), cows are given a score of 0.5 from 1 to 5, and cows with a score of 3.5 and above are considered clinically lame. However, the method has some difficulties. These are that the system is difficult to learn, the first five point steps (1.0-3.0) are given to cows that are not clinically lame, and the cow is scored during the transition from the lying position to the rising position (Juarez et al., 2003; Nordlung et al., 2004). Sprecher et al. The method developed by (1997) is mostly suitable for free type barns and is very useful in determining the severity of lameness and its prevalence in the herd quickly, easily and accurately. During the scoring, evaluations are made according to the shape of the back of the cow while walking and standing, the way it walks and its weight on the feet. Cows are given a lameness score (TP) ranging from 1 (normal) to 5 (very lame) (Figure 1). According to the scoring method, 1 point (normal): cows with straight back lines and normal gait during standing and walking, 2 points (slightly lame): cows with straight back lines when standing, hunched when walking but considered normal to walk, 3 points (moderately lame): cows with a hunched back while standing and walking and one or more strides when walking, 4 points standing hunched and slouched (cows with one or more strides) cows that throw and try not to put too much weight on one or more of their feet; 5 points (severe lameness): awarded to cows whose backs are humped while standing and walking and who have difficulty or are very reluctant to put weight on one or more feet. Researchers who developed this method (Sprecher and Kaneene, 1997) stated that cows with TP 3 were at the border between subclinical and clinical. It is shortening in various studies, trying to step on the unaffected side of the sole of the foot to carry its weight, decreasing walking speed and stopping frequently to rest the aching foot while walking. Using different combinations of these movements, different lameness scoring systems have been developed for dairy cattle. There are important implementation differences between scoring systems.

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Batch et al., 2007) cows with TP ≥ 3 were considered lame. Robinson (2001) stated that the lameness score is a qualitative index of the normal walking status of cows. A lameness score above 1 is not an indicator of the cause of lameness. A score above 1 indicates that the causes of lameness at the individual or group level should be determined and necessary actions should be taken for treatment (Juarez et al., 2003).

Lameness in dairy cattle has a negative effect on fertility, milk yield and various behaviors. In a recent research project, the implementation of 3D depth video technology was utilized to identify early signs of lameness in dairy cows. (Abdul Jabbar et al., 2017). The cow's body was captured in a top-down 3D image, which enabled the segmentation of high curvature features such as its bones and spine. Afterwards, the segmented regions were tracked, leading to the extraction of motion values in the form of height measurements from the monitored areas.. This value was further analyzed as gait asymmetry to assess mobility and detect early lameness. As a result of the study, 100% sensitivity in the detection of lame cows, 75% specificity in the detection of non-lame cows and 95.7% accuracy in the overall success rate were obtained using the Support Vector Machine (SVM) classifier.

3. IMAGE PROCESSING

It is possible to define Image Processing as three-dimensional objects being detected by the sensors, transferred to the computer, and transmitted to the imager output by performing any operation on it.

Image processing today; It is used in many fields such as medicine, agricultural activities, military, security and traffic. In this article, it is aimed to determine the lameness of cattle from the angles they make between their bones.

Many projects on image processing have been made so far and most of them have been successful. Numerous studies in the literature demonstrate how these technologies can be instrumental in observing both typical and atypical behaviors of animals. One example involves employing radio frequency systems to track animal movements, yielding valuable insights into the feeding and drinking behaviors of cattle. (Sowell et al., 1998; Quimby et al., 2001; Wolfger et al., 2015; Shane et al., 2016). Furthermore, this technique has found extensive application in evaluating animal movement and identifying signs of lameness. (Nielsen et al., 2010; Grégoire et al., 2013; Conte et al., 2014; Rutten et al., et al., 2013; Schlageter-Tello et al., 2014; Van Nuffel et al., 2015). Nonetheless, the utilization of sensors attached to animals for behavior monitoring can induce stress and, in certain instances, may prove impractical for assessing group behavior due to cost and susceptibility concerns. Machine vision has emerged as a widely accepted alternative solution in numerous agricultural and industrial processes. (Shao and Xin, 2008; Costa et al., 2014; Nasirahmadi et al., 2016b; Oczak et al., 2016).

Automated computer imaging systems can help both farmers and researchers find solutions to animal tracking problems. For example, live weights and welfare levels of animals can be determined by making more objective and continuous measurements through image processing techniques instead of manual methods, which are both time-consuming and costly. Computer vision, or machine vision approach, is a cheap, easy, stress-free and non-contact method that can be adapted to different animals in both indoor and outdoor environments by using the natural characteristics of animals (shape, color, movement).

4. METHOD

In the first stage, YOLOv5, which uses the YOLO algorithm, was used for the detection of cattle. The utilization of the YOLO algorithm is justified by its ability to rapidly and efficiently detect objects in a single pass. Its superior speed compared to other algorithms is attributed to its capacity to process the entire image through a neural network simultaneously. YOLOv5 is a PyTorch implementation unlike other YOLO versions. As in YOLOv4, CSP (Cross Stage Partial Networks) backbone and PA-NET neck are used. In the head part, the model used in YOLOv4 is used. As the activation function, Leaky ReLU and Sigmoid are used. YOLO v5 incorporates the Leaky ReLU activation function in the middle/hidden layers, while employing the sigmoid activation function in the final detection layer. Additionally, the default optimization function used for training in YOLO v5 is SGD (Stochastic Gradient Descent). Pose prediction application was made using OpenPifPaf for detected and followed cattle. OpenPifPaf is a Python application. In this development process, we focused on the model and the data set, and it was aimed to increase the success of the model with the correct labeling and correct data augmentation in the data set. Here, the training code that YOLOv5 gave us will be used and after our training, two model will be prepared. YOLO (You Only Look Once) algorithm works faster when compared to CNN algorithms. Although there are fast-running algorithms other than YOLO, mAP (mean absolute precision) values are insufficient. YOLO can detect in real time and its average precision (mAP) values are sufficient. That's why we made it with YOLOv5. Performance analysis of the dataset used for the detection and labeling of Yolov5l 200 epoch cattle is shown in Figure 1 and Figure 2.

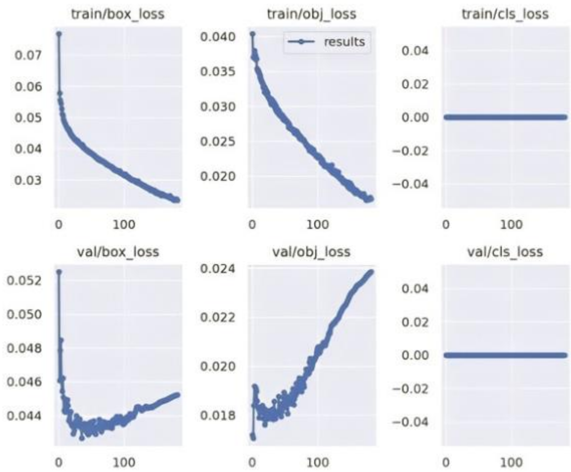

Figure 1. Performance analysis

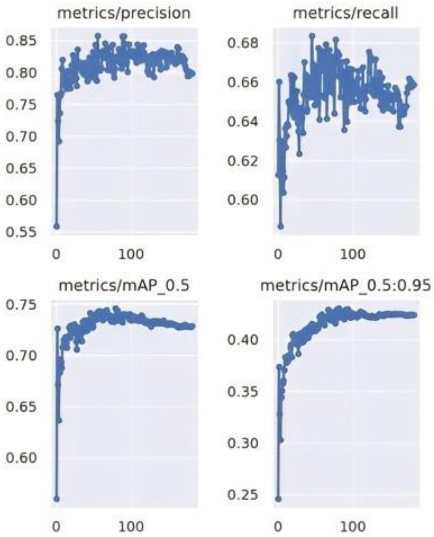

Figure 2. Performance analysis -2

We first complete our training in system architecture. Then we get our images to be processed. We perform object detection to detect our cattle in these images. We label our detected cattle. Posture estimation in cattle and then calculation of angles will be realized by performing mathematical operations on the posture formed from this estimation. From these calculated angles, early detection of lameness will be ensured. These steps are shown in Figure 3.

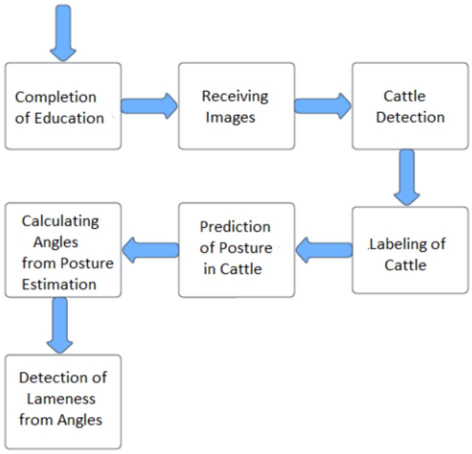

Figure 3. System architecture

4.1. Obtaining the Data Set

The dataset was obtained from the Open Image Dataset v6 cattle class. Using Roboflow, data augmentation was done in the data set and our data set was easily output according to the frameworks we wanted. Our dataset includes images of a single cattle, multiple cattle and cattle at a distance. In Figure 4, sample images from the data set are presented.

Figure 4. Data set

4.2. Object Detection

The object detection phase determined on the videos consists of two steps. In the first step, the object is highlighted. In the second step, the object is separated from the background. Appearance and shape properties are often used as the basis for object detection. Object detection is the stage that determines the selection of an appropriate algorithm for tracking the object. The object detection phase is more important as it affects the success of the next phases. The methods used in the detection and tracking of the object; They are YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), R-CNN (Region Based Convolutional Networks), Fast R CNN, Faster R-CNN, Mask R-CNN (Ozbaysar & Borandag, 2018). R-CNN performs object detection by combining two approaches. The first is to generate region suggestions for the object, and the second is to apply a convolutional neural network to the region suggestions (Girshick et al., 2016). The extracted region suggestions are classified using Support Vector Machines (DVM) (Daş et al., 2019). YOLO optimizes the problem end-to-end with a single neural network and detects objects directly according to its detection performance (Redmon et al., 2016). It is one of the popular algorithms for object detection, especially in recent years. Speed is an important concept in object detection. What distinguishes YOLO from other algorithms is its real-time object detection. SSD performs object recognition at once using a single deep neural network and works faster than Faster R-CNN (Liu et al., 2016). Some improvements have been made to address the shortcomings of other methods. These improvements increase speed by allowing the SSD to match the accuracy of Faster R-CNN using lower resolution images. The YOLO algorithm is extremely fast. During both the training and testing phases on the dataset, YOLO processes the entire image as a whole. Consequently, it implicitly embeds contextual information regarding classes and their visual characteristics, enhancing its ability to recognize objects with contextual cues. By learning versatile object representations, YOLO gains a competitive edge over other leading detection methods when subjected to training and testing on real-world images, consistently achieving superior performance. The YOLO algorithm utilizes bounding boxes to encircle the detected objects in the images. The input image is divided into grids of various sizes, such as 5x5, 9x9, 17x17, and so on. Each grid assesses the presence of an object within it and determines whether the object's center point falls within its designated area. Once the grid identifies the presence of an object's center point, it proceeds to determine the object's class, height, and width, subsequently delineating a bounding box around the detected object. An example YOLO Bounding box representation is presented in Figure 5.

Figure 5. YOLO Bounding box representation

The YOLO (You Only Look Once) algorithm was introduced by Joseph Redmon in 2015. YOLO is used for real-time object detection. This algorithm detects objects in the image as boxes by forward propagation. The architecture of the YOLO algorithm is given in Figure 6.

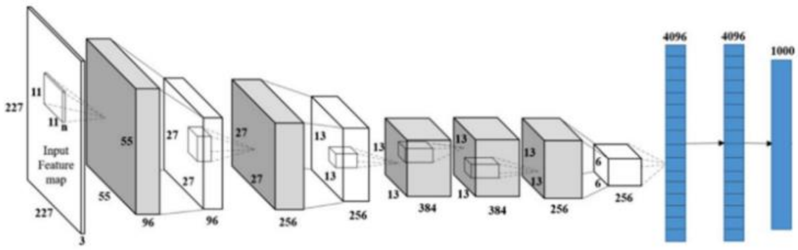

Figure 6. The architectural structure of the YOLO algorithm

4.3. Image Preprocessing (Data Augmentation)

These are the pre-processes to make the data ready for processing in the data sets created according to the determined categories. Preprocessing consists of steps that attempt to correct or compensate for systematic errors and operations that prepare data for subsequent analyzes. Digital images are subjected to various corrections such as geometric, atmospheric. All these fixes may not be applied in all cases. These errors are systematic and can be removed before they reach use. Images were preprocessed to train the model against alternative situations. In cases where perfect camera view is not possible or color saturation may vary, image preprocessing has been done in order to adapt to these situations and increase model performance. Image preprocessing was done using Roboflow application. Roboflow application provides us with many conveniences. You can directly load the source data set, select the operations and perform augmentation operations. As seen in Figure 7 and Figure 8, different augmentation processes have been added.

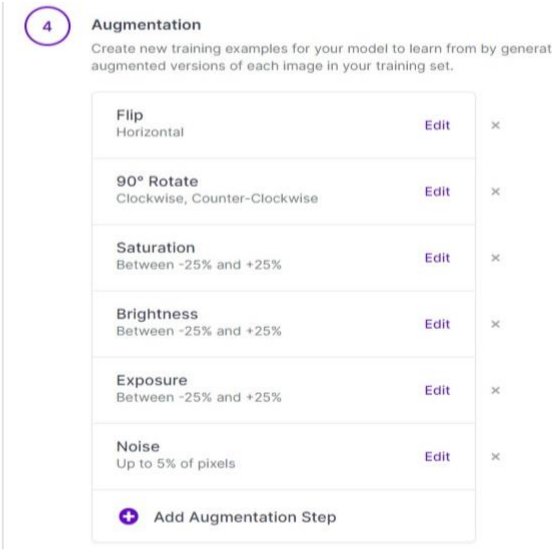

Figure 7. Augmentation processes-1

With Roboflow, we can do the sizing according to our wishes. Conversion has been applied for the sizes of the files in the data set. The following preprocessing was applied to each image:

• Resize (Extend) to 416x416

• Automatic orientation of pixel data (with EXIF-oriented peeling)

• The following magnification was applied to create 3 versions of each source image:

• Random exposure setting from -25 to +25 percent

• 50% horizontal flip possibility

• Salt and pepper noise was applied to 5 percent of the pixel.

• Equal probability of one of the following 90 degree turns: none, clockwise, counterclockwise Random brightness adjustment from -25 to +25 Percent

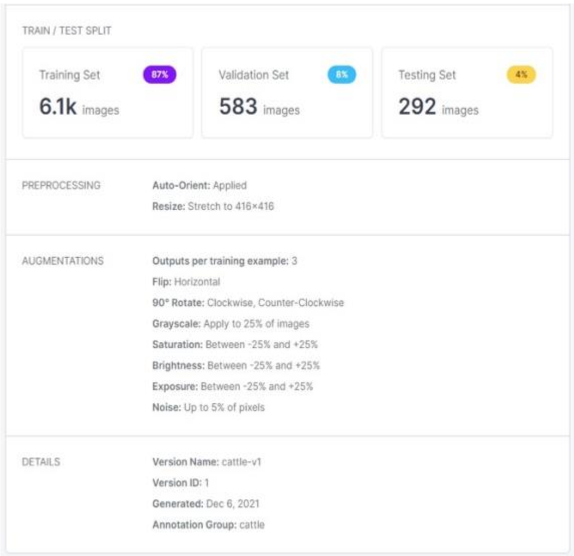

Figure 8. Augmentation processes-2

Figure 9 presents the data augmentation and digitization stages. In Figure 10, there are pre-processed visuals made during the studies.

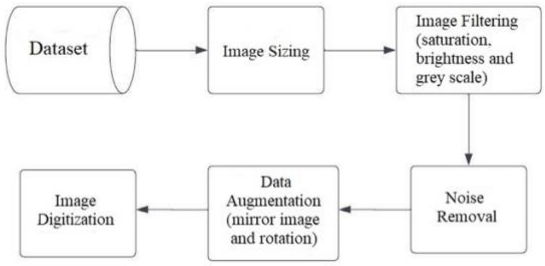

Figure 9. Data augmentation and digitization stages

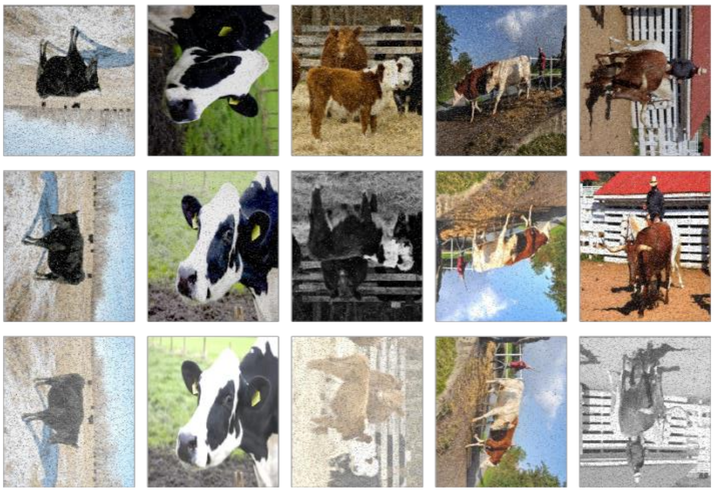

Figure 10. Pre-processed visuals made during the studies

4.4. Pose Estimation

Pose estimation is a fundamental computer vision task aimed at deducing the position and orientation of a subject or object from an image or video. It is akin to camera pose estimation, wherein the objective is to ascertain the relative position and orientation of a camera concerning a specific creature or object. Typically, this process involves the identification, localization, and tracking of a set of key points on the subject or object of interest. These key points can pertain to vertices or other significant features, enabling effective pose estimation and tracking for both objects and creatures. And for living things, these key points represent large joints such as the elbow or knee. With exposure estimation, we can track a real-world object or creature at an incredibly detailed level. This remarkable capability expands the horizons for various potential applications. Additionally, exposure estimation distinguishes itself from other prevalent computer vision tasks in several crucial aspects. For instance, object detection revolves around locating and identifying objects within an image. Nevertheless, in the context of object detection, the localization is usually at a coarse-grained level, involving a bounding box that encompasses the object. Exposure estimation goes further by estimating the precise location of key points associated with the object.

Figure 11. Posture estimation

4.5. Determining the Angle

After the object detection, data augmentation and pose estimation stages we had done before, we carried out our work on the angle finding part. We did a literature search. And as a result, we realized that there was no previous example in the literature, and since there is no such example, we tried to perform the angle finding process on cattle by looking at other examples. We performed the angle calculation part on the images that we applied pose estimation. We used the keypoints (coordinates) in the image we applied pose estimation and the success rates of these keypoints. If the keypoint success rate is not zero, we calculated the angle from the coordinates in the posture, and plotted the calculated angle on the image using the Python PIL library. Python PIL library is an open source graphics processing library. It is a library developed to easily perform image operations in Python.

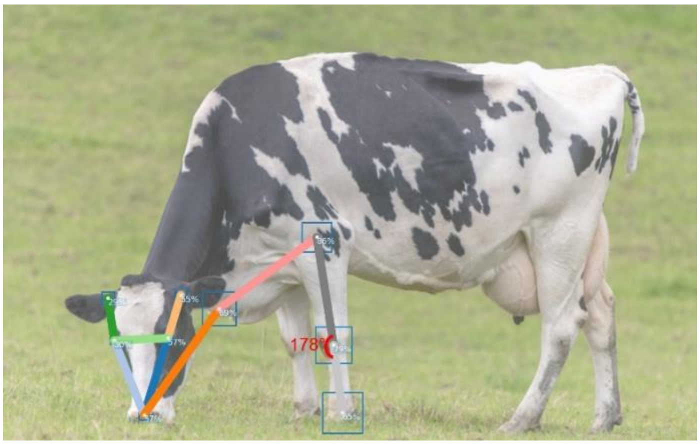

Figure 12. Determining the angle

In Figure 13. the angles in the legs of a cattle were determined.

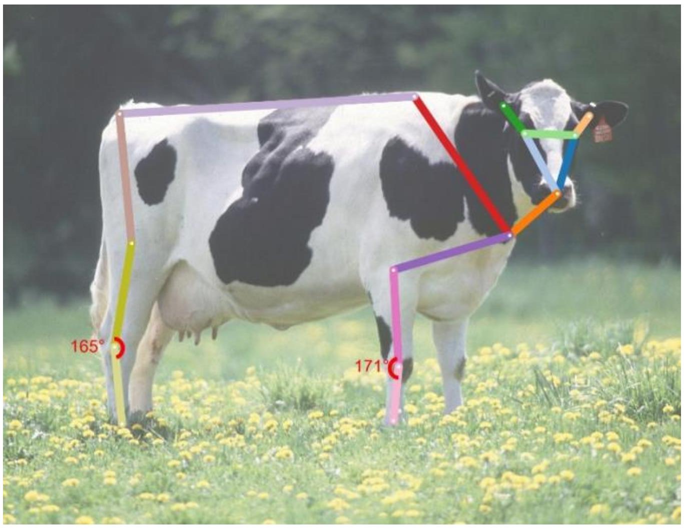

Figure 13. Determining the angle – 2

5. CONCLUSIONS

In this article, we first needed to obtain a data set. The dataset was obtained from the Open Image Dataset v6 cattle class. Afterwards, the data was preprocessed. This process is the pre-processes to make the data ready for processing in the data sets created according to the determined categories. In cases where perfect camera view is not possible or color saturation may vary, image preprocessing has been done in order to adapt to these situations and increase model performance. Image preprocessing was done using Roboflow application. Roboflow application provides us with many conveniences. You can directly load the source data set, select the operations and perform augmentation operations. The YOLOv5 algorithm was used for the detection of cattle. YOLO can detect faster than other algorithms. This is because it passes the entire picture through a neural network at once. Thanks to the opportunities offered by YOLO, the identified cattle were put in a bouding box. Finally, posture estimation was made in cattle using openpifpaf. We performed the angle calculation part on the images that we applied pose estimation. We used the keypoints (coordinates) in the image we applied pose estimation and the success rates of these keypoints. If the keypoint success rate is not zero, we calculated the angle from the coordinates in the posture, and plotted the calculated angle on the image using the Python PIL library. This article will contribute to the work to be done in the image processing and agriculture sector. Since there are not many studies on this subject, it is a source for future studies.

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