IJAS Iranian Journal of Applied Animal Science

Recognition of Hereford and Simmental Cattle Breeds via Computer Vision

Research Article

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Received on: 22 Jul 2022
Revised on: 22 Sep 2022
Accepted on: 15 Oct 2022
Online Published on: Mar 2023

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Online version is available on: www.ijas.ir

ABSTRACT

Self-sufficient unmanned systems like computer vision products increasingly become essential in managing the data and supporting producers in making decisions in the livestock environment. Image classification is one of the most famous missions for machine learning (ML) methods and its goal is to detect the objects in the frames. The main objective of the research was to investigate whether the classification of two breeds, Hereford and Simmental, often confused with each other due to their morphological similarities, via image processing, is helpful in the case of livestock production. 600 images of different individuals from Hereford (300) and Simental (300) cattle breeds were included in the study. The Fully Connected Neural Networks (FCNN) were established estimate the breeds. Modelling of artificial neural networks, image processing and all other analyses was conducted with EBimage and Keras packages in R language on a PC with 11. Gen. i7 CPU and CUDA supported GPU model of RTX 3060. The results show only 17 were inaccurate in 600 images in total with an accuracy greater than 97%. The training process of the model was executed in 69 seconds. At the end of the investigation, it was clarified that the use of FCNN in livestock would be beneficial in terms of breed classification via image recognition.

KEY WORDS artificial intelligence, cattle breed classification, computer vision, Hereford and Simmental, image recognition, neural network.

INTRODUCTION

The cattle presence in Turkey, which was at the level of 10 million heads in 2000, has exceeded the level of 18 million by 2021 (Türkiye İstatistik Kurumu, 2021). The difficulties created by such a large data flow in data recording, tracking, analysis and synthesis in herd management increase the need for robotic systems. Considering the increased workload due to rapidly increasing data volume and level of automation as a result of the increasing animal presence and requirements of today's industrial livestock, further research on individual identification, determination of age, body condition score, image recognition and classification with machine learning required in terms of tracking such a large-scale data. Various tag identification methods have been applied for many years in animal identification (Bowling *et al.* 2008; Felius *et al.* 2011). Determination of individual animals has become mandatory in precision farming. Automated collection and processing of data allow different types of knowledge which can be analyzed into numerous documents and helps the farmers to get informed in terms of herd management. The identification of cattle breeds is one of the most challenging obligations in today's industrial livestock. From this point of view, many studies are being carried out on dairy research. But the sufficiency is not that entirely, and existing techniques are expensive and not effective either such as radio frequency identification (RFID) and Muzzle pattern recognition (MPR) and even sometimes being harmful to the animal. Therefore, cost-effective and self-sufficient unmanned systems like image-processing drones gain more importance day by day in terms of collecting and analysing the data and helping the producers make decisions.

Artificial intelligence and computer vision have wide use in different disciplines such as medicine, agriculture, microbiology, pharmacology, livestock and even in the national defense industry, etc. Image classification is one of the most popular tasks for machine learning (ML) methods and its purpose to identify the objects in a frame. For instance, image classification could be easily applied to predict whether there is a calf or any other object in the image or not. The process can also be used to solve different kinds of prediction, classifying, determination or optimization problems. According to Borges *et al*. (2021), some deep learning methods using various types of strategies or architecture have been proposed for image recognition. One of the first deep learning architectures proposed used fully connected and convolutional layers to deal extraction of traits and classification on a single model. Such structure brought a leap in performance which began a revolution in image processing (Borges *et al*. 2021).

Wu *et al*. (2020) reported they observed an accuracy of 98, 57% to classify lameness via long-short term memory (LSTM) is used for the classification of categorical data. Last developments in the computer vision field, artificial neural networks have been rapid growth especially in the field of localization, face recognition and classification techniques (Zhang *et al*. 2020).

Simmental and Hereford breeds are often confused with each other due to their morphological similarities. Figure 1 shows the typical side view of the two breeds. Morphological traits can be used to classify artificial identification of breeds which includes the information of distinctive features by breeds in images. Furthermore, the identification of individuals is possible. Cattle breed detection and classification are achieved by using image processing techniques. Many image classification algorithms create an area on the image and change this area in the image, crossing all pixels and classifying the recorded images through neural networks. Fully connected networks are one of the most widely used classification techniques and have the wide application (Too *et al*. 2019).

From animal breeding point of view, data collection and recording of the animals is necessary and cannot be replaced by. The main purpose of this study is not individual diagnosis, but classification of two breeds. Therefore, it would be appropriate to mention the use of the present technique in some specific aspects of animal breeding. Although Simmental is one of the combined yield-oriented breeds and the other breed Hereford beef cattle, they are often confused each other with the human eyes due to their morphological similarities. But this distinction can be made more practically and decisively with the technique used in our study. In addition, it will be even easier to classify with this method by looking at some morphological features such as rump structure, leg length, angle and ratio, height of the breast, rip angle and spacing etc., which are frequently used in animal breeding (Göncü, 2020). In this way, it should be mentioned that the use of this method in breeding, selection and crossbreeding will be appropriate, like the determination of dairy type characteristics in cattle or selection of the sires for next generation. Because with present method, the distinction of all phenotypic features reflected in the external appearance can be made in a practical, stable and accurate way. In other words, breeds can also be sub-classified according to their external appearance. However, this will require much more large sized datasets of images and even databases from different geographies, otherwise it is difficult to obtain sufficient variation for selection with a limited dataset. Different studies that reflect the distinctive morphological characteristics of individuals are required in order to be able to make an individual identification. The main objective and novelty aspect of this study is to focus on the use of fully connected neural networks (FCNN) for classification of these two breeds with image processing that haven't been studied before which is one of the machine learning methods used in especially binary image classification and doesn't require uniform posing or shooting standardization. Breed classification will be possible thanks to the current technique by digitizing the visuals and eliminating the random errors. In other words, details that the human eye cannot categorize can be classified by analyzing the digital data.

MATERIALS AND METHODS

The material of the study consists a total of 600 images of different individuals obtained from Hereford (300) and Simental (300) cattle breeds. The photos were taken from 20 different fully intensive enterprises operating in Türkiye in 2020 and 2021 within the scope of Technological Applications in Livestock project. Side view shots which are clean in terms of noise, blur, high contrast and occlusion to prevent the under fitting of adult and standing cattle under sufficient light during daylight hours were preferred. 375 of the raw images were captured by a 10.2-megapixel Nikon D3000 camera with an 18-55 mm lens, and 225 of them were obtained by smart phones have 10 to 48-megapixel camera with a fixed lens and grouped by an expert, zootechnician, according to the morphological characteristics of the Simmental and Hereford breeds. Randomly selected 10% of the dataset is represented in Figure 2.

Figure 1 The typical side view of the 2 breeds
* Breeds belong to the images are Simmental, Simmental, Hereford, Hereford from left to right respectively

Figure 2 Randomly selected 10% of the dataset

Morphological characteristics of Hereford cattle

They are well muscled and bodied due to their beef yield, long length from the side, length of the leg is adequate, large in size, trim and smooth. Adult females may weigh around 500-600, while males may weigh up to 850-900 kg. Most animals have thick and short-horned that is typically curved down around the sides of the head, but there is a polled variety in America and UK (Polled Hereford). Its some varieties are usually colored dark red to yellowish red with a white face, dewlap crest and underline. Herefords with white markings and white flanks below the knees. Hocks are also seen commonly. Their back, waist and hind quarters or round precious cut areas are also well developed. The Hereford color is quiet characteristic with the body color differs from dusty brown to a deep variation in red. Legs below the hocks are typically white and face, crest, dewlap, underline and switch.

The prominent white face tends to dominate in crosses with other breeds and can have been a trait in setting popularity of the breed up (Ensminger, 1990; Felius *et al.* 2011; Göncü, 2020).

Morphological characteristics of Simmental cattle

Simmentals are muscled animals, long and deep-bodied with strong bone. Simmental color varies from red to gold with whiteness, and could be evenly distributed or identified in patches on a white frame. The head is often white and often a white band appears between the shoulders like in the images given in Figure 1. They commonly show colored pigment around the eyes, which helps to decrease problems of eyes which may be seen in case of strong sunlight. Ideally the hair is soft and not long as Hereford's. They can rarely be seen with red pigmentations about the eyes and white patches behind the shoulders and over the flank. Simmentals' color varies from straw to brown color even to dark red sometimes with white marks around the belly, legs and over the head. The breed is naturally horned even if breeders are producing polled Australian purebred cattle. They have an excellent temperament and satisfying with milk production due to their combined efficiency in yield (Ensminger, 1990; Ozkutuk and Sekerden, 1990; Göncü, 2020).

Analyzing the data

The analyses were executed on a PC that has a model of i7 11700 processor and CUDA supported GPU model of RTX 3060 with 12 GB VRam, 32 GB DDR4 3600 Mhz Ram. Image processing and analyzes of the current research were carried out with EBimage and Keras -by using the TensorFlow GPU version as a backend- packages in R which is a free and open access programming language prior for statistical purposes. Keras' package in R runs on both 'CPU' and 'GPU' devices and was developed with the focus on allowing fast experimentation, supports both recurrent networks (as well as combinations of the two) and convolution-based networks. Image supplies general goal functionality in image analysis and processing. EBImage offers tools to segment cells and extracts countable cellular descriptors in the case of (high-yield) microscopy-based cellular assays. This suggests the automation of such tasks by using R language and facilitates and the use of other tools in R environment for deep learning, signal processing, computer vision, statistical modeling and visualization with image (Pau *et al.* 2010).

The images were first converted into digital data with the EBimage package and rescaled in 128x128 pixels to make them suitable for analysis. Then these 128 × 128 dimensional matrices were reshaped for colored image analysis by converting into a single vector of 128 × 128 × 4 size. Finally, the classification of the photographs was carried out with the fully connected neural networks (FCNN). A digitized version of the images and the basic architecture of FCNN are given in Figure 3 and Figure 4 respectively.

Fitting the model

The sequential model was used in the modeling of the network and the activation function of the hidden layers and the output layer were preferred "ReLU" and "Softmax" respectively as there are 2 types of breeds, Hereford and Simmental (Asadi and Jiang, 2020).

There are 65536 neurons in the input layer and 2 hidden layers with 256 in the first and 128 neurons in the second one. ReLU function was applied as activation function in the hidden layers. There are 2 neurons in the output layer since there have been 2 different breed classifications (Table 1).

Rectified linear unit (ReLU) layer

It adds non-linearity to the system. It is the layer where the activation function is applied. Negative values are set to zero and positive values are retained. The convolution layer has a linear structure. This layer is applied to transform the mesh into a non-linear structure. Using this layer, the network learns faster. It allows only active features to be moved to the next layer (Inik and Ulker, 2017).

Softmax function, also known as softargmax or normalized exponential function is a function that takes input as a vector, then normalizes it into a distribution of probability consisting of probabilities to the exponents of the input. The main purpose of using a Softmax function is to classify the images with a probabilistic variable between zero and one (Bello *et al.* 2020). Overfitting was tried to prevent via reducing the complexity of the network by regularization of the model, augmentation of the data and early-stopping while training (Piotrowski and Napiorkowski, 2013).

According to Soydaner (2020), root mean squared propagation (RMSProp) algorithm was used as the optimization function. One of the algorithms that modify AdaGrad is RMSProp. It is applied to perform better in a non-convex setting via changing the gradient sum up into an exponent weighted moving mean. AdaGrad shrinks the learning rate according to the whole history of the squared gradient.

Soydaner (2020) reported that Goodfellow (2016) indicates RMSProp uses a decaying average of the exponent to discard history from the outlier data points so that it can converge fast after finding a convex bowl.

According to Soydaner (2020), squared gradient is summed up to execute RMSProp after the calculation of the gradient:

$$r \leftarrow \rho r + (1-\rho) g \odot$$

Where:

ρ: decay ratio.

Then the parameter update is calculated and carried out as:

$$\Delta\theta = -\frac{\epsilon}{\sqrt{\delta + r}} \odot g$$

$$\theta \leftarrow \theta + \Delta\theta$$

Where:

ϵ: learning rate.

δ: small constant for numerical balance, r for gradient accumulation.

For training the model, 480 (80%) of the photographs were reserved for the training set, for performance evaluation, 120 (20%) were reserved for the test set.

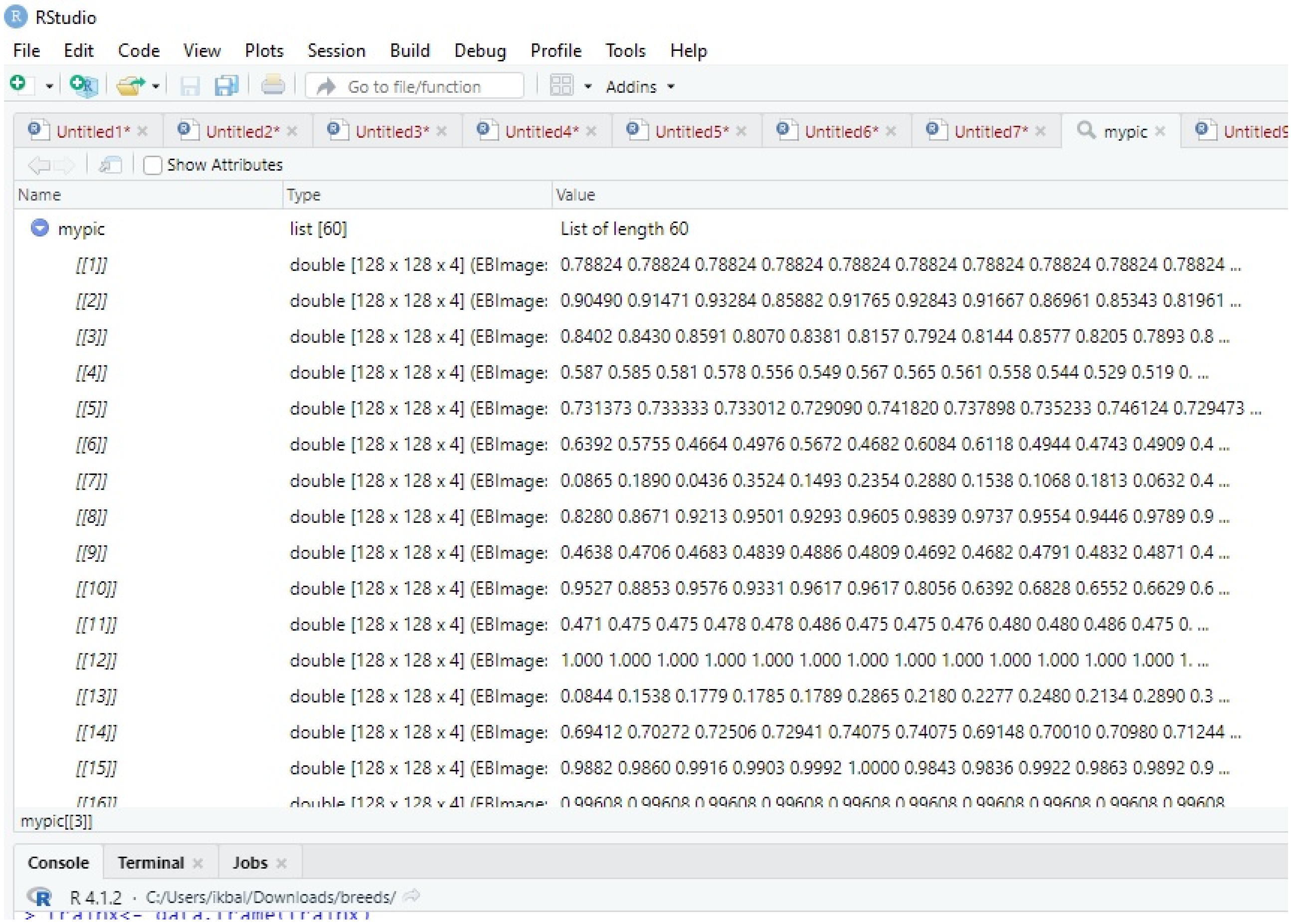

Figure 3 The digitized version of images to bring ready to analyze

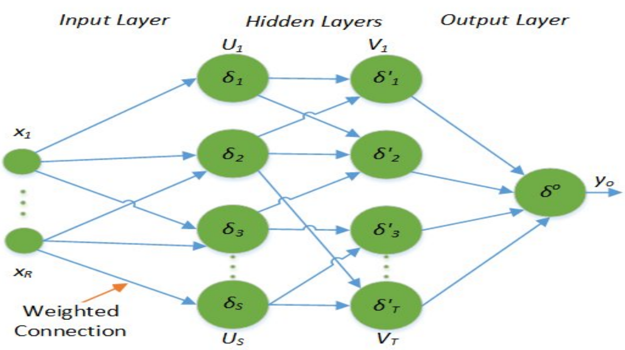

Figure 4 The basic architecture of an Fully Connected Neural Networks (Haider *et al*. 2019)

Table 1 Summarize of the model

Model: "sequential"		
Layer type	Number of Neurons	Parameters
Input Layer	65,536	
1. Hidden Layer	256	16,777,472
2. Hidden Layer	128	32,896
Output Layer	2	258
Total parameters: 16,810,626		
Trainable parameters: 16,810,626		
Non-trainable parameters: 0		

Table 2 Calculation of the accuracy, precision, sensitivity (Recall), specificity to the performance of the model according to breeds

Formula	Evaluation target
$Accuracy = \frac{TP+TN}{TP+FN+FP+TN\ TP}$	The ratio of correctly predicted images over the total number of images
$Precision = \frac{TP}{TP+FP}$	The proportion of correctly classified positive samples to the number of samples labelled as positive in the data. The proportion of the positive (Hereford) results that were correctly classified. In other words, the proportion of the correctly classified images belong to Hereford breed.
$Sensitivity\ (Recall) = \frac{TP}{TP+FN}$	The ratio of correctly classified positive samples to the number of positive samples in the data
$Specificity = \frac{TN}{TN+FP}$	The proportion of correctly classified negative samples to the number of negative samples in the data

TP: true positive; FP: false positive; TN: true negative and FN: false negative.

Guyon (1997) indicates that only 10% of the training data is sufficient if the data size is greater than 1000, otherwise 20-25% should be reserved for validation. So validation split was preferred %20 as there are 600 images in total for the data set. Fitting Model preferred as number of iterations 100 while batch size equals 64.

Evaluation of the model

As Sokolova and Lapalme (2009) mentioned that accuracy, precision, sensitivity (recall), specificity are most commonly used measures for the evaluation of the classification methods in their study about the performance measures for classification tasks. So these measures of the model were computed for the train and test data as the main criteria in terms of the evaluation of the model.

Accuracy, precision, sensitivity (Recall), Specificity of the model were calculated in terms of identifying the other performance parameters. The main evaluation criteria and their formulas are represented in Table 2 to test the main performance indicators of the model. True represents the actual observations and False the predicted ones while Positive stands for the Hereford breed and Negative for the Simmental.

True Positive (TP) means number of correctly predicted Hereford observations which are observed actually Hereford. False positive (FP) represents the number of inaccurate predictions of Hereford which are observed actually as Simmental while false negatives (FN) the number of inaccurate predictions of Simmental which are observed actually as Hereford. True negatives (TN) represents the number of correctly classified negative predictions which is actually Simmental observations.

Probabilities belong to the individuals of the breeds were also evaluated for deeply analyze the breeds at the level of individuals to understand the underlying fundamentals of the incorrect predictions. Accuracy stands for the ratio of correctly predicted images while probabilities for how much chance to be predicted for each observation there is.

Loss shows the model's error, which is the absolute difference between expected and observed values. The execution time of the processor for whole model training was observed as well in terms of inferencing about both dealing with big data and the cost-effectiveness of the TensorFlow GPU version for the training process, stands for the time difference between the start and end of the training process.

RESULTS AND DISCUSSION

The results show that 583 (295 for Hereford, 288 for Simmental breeds) images over 600 were accurate predictions with a percentage of 97,17 in a total of train and test datasets. Table 3 represents actual observations and predicted ones according to breeds.

Performance indicators of the model

It has been determined that, since working with a data set consisting of 480 observation values in the learning process, the errors converged to 0 for training and validation from the 60^{th} iteration. The accuracy rate started to stabilize around 80% from the 70^{th} iteration for validation, and around 100% from the 60th iteration for training (Figure 5).

The number of iterations would change as the number of validations will change depending on the batch size in case of modelling is performed on a larger sample set. The increase in the number of observations decreases the number of iterations during learning process according to a study about the size of the sample dataset for image classification conducted by Liu and Deng (2015). Accuracy, precision, sensitivity (recall), Specificity were found to be as 97.17%, 96.09%, 98.33%, 96.00% respectively (Table 4). The highest performance indicator was observed as 98,33% sensitivity which means the proportion of correct positive predictions divided by total number of actual Hereford observations while the specificity, the proportion of the correctly classified negatives (Simmental) over the total actual Simmental observations was found to be 96%.

Table 3 Confusion matrix[1] belong to the performance of the model according to breeds

		Expected (predicted)		Observed total (actual)
		Hereford (positive)	Simmental (negative)	
Observed (actual)	Hereford (positive)	295 (TP)	5 (FN)	**300**
	Simmental (negative)	12 (FP)	288 (TN)	**300**
	Expected total (predicted)	**307 (TP+FP)**	**293 (FN+TN)**	**600**

[1] Observed stands for actual observations while expected for predicted ones.
TP: true positive; FP: false positive; TN: true negative and FN: false negative.

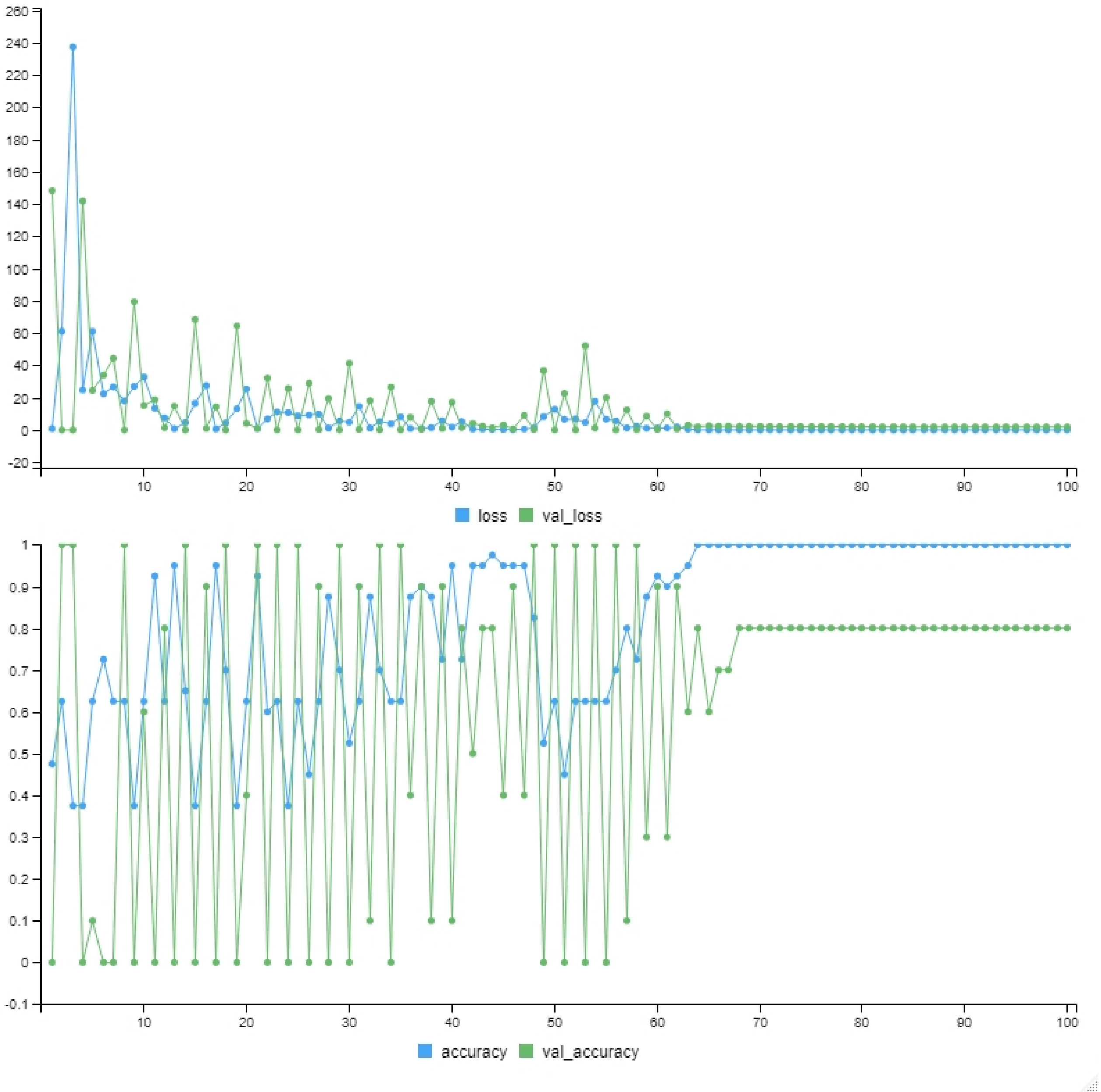

Figure 5 Change in accuracy and loss according to training and validation while the learning process

Table 4 Performance indicators of the model

Indicator	Performance
Accuracy (%)	97.17
Precision (%)	96.09
Sensitivity (%)	98.33
Specificity (%)	96.00

Table 5 Performance of the model

Item	Accuracy %	Loss	Execution time (secs.)
Train	97.92	0.11	69
Test	94.17	0.14	

The proportion of correct positive (Hereford) predictions divided by the total expected number of Hereford predictions is 96,09% (precision).

The accuracy rate and error of the model belonging to the train set were 97.92% and 0.11%, the test was found to be 94.17 and 0.14, respectively (Table 5). It was observed that the training process was completed in a total of 69 seconds. Cevik and Boga (2019), in their study on body condition score determination by image classification method, states that the performance parameters of the network created with the Ale × Net architecture are 100% accuracy for the train and 63.64% for the test, and the training process is completed in 197 seconds. While these values were similar to the accuracy rate for the train (97.92%) of the current study, it was found to be lower for the test set (see Table 5, Test accuracy 94.17%) and the total training time was higher. Model performances vary, as the subject materials of both studies differ. Apart from that, it is known that performances of the predictions may vary due to sampling size, subject material, the architecture of the model used even the specifications of computers.

The accuracy rates between the train and test sets were not similar (100% for train and 63,64 test) in the study conducted by Cevik and Boga (2019). Likewise, it is understood that the accuracy rate of the current study for the test set is higher than their study. Since the difference between Train and Test accuracy rates may be due to overfitting during the training process or distortions of images in the test data, Train and test accuracy rates are expected to be similar.

Similar to our research results in the current study; Weber *et al.* (2020) indicates that they found the highest accuracy for individual identification of Pantaneira cattle is 99,74% for train, 99,86% for test and 13 hours and 14 minutes execution time which is a higher accuracy and execution time than current research may due to not only their large number of dataset but also the difference of the research content (individual identification) than ours (classification of two breeds). Qiao *et al.* (2019), reported that they got 91% accuracy with a number of 20 frames in their research about individual identification via combining LSTM and the convolutional neural networks (CNN, Billah *et al.* 2022), shows the best accuracy in their study about individually recognition of goats was 96.4% which is similar with ours 97.92.

It has been determined that the model performs a higher accuracy rate for the training (98.75%) and test (96.67%) in the classification of the Hereford breed compared to the other breed (Table 6).

This suggests that the Simmental breed shows high variation during image processing and the Hereford breed can be classified more successfully by image processing (Bene *et al.* 2007; Borges *et al.* 2021). But that means Simmental may have an advantage in terms of individual identification from their standing side view shots due to its higher variation. The average, standard error, variance, and variance analysis results of the photographs converted into numerical data during image processing are represented in Table 7.

Accordingly, it was seen that the Simmental breed (0.11) showed higher variation in their appearance than Hereford (0.09), and there was a statistically significant difference at the 0.001 significance level between the means of the breeds. The results show that 90% of the observations on the test set and more than 95% for the train were predicted correctly with a probability greater than 99%. It is found that out, images that belong to about 97% of Hereford and 92% of Simmental breeds respectively in the train set and more than 93% and around 87% in the test are predicted correctly with a probability of over 99% (Table 8). It is determined that 6 over 7 images (numbered 244, 254, 558, 567, 574, 581) that were incorrectly estimated in the test set have a probability of 40-50% (Figure 6 and Figure 7). In addition, it was observed that the model did not give a chance to any image in the range of 50-60% among estimation. This suggests that the model classifies with definite limits and may be caused by distortions such as noise during recording or grouping error due to observer. Massouh *et al.* (2017) reported that the presence of noise, blur, contrast and occlusion affects the classification accuracy of deep neural networks. Also, da Costa *et al.* (2016) and Dutta *et al.* (2012) reported that the small number of distortions could affect image recognition procedures. Koziarski and Cyganek (2017), from their research named "Image recognition with deep neural networks in the presence of noise dealing with and taking advantage of distortions". It is understood that noise and other distortions that negatively affect image quality affect the probability of expected outputs.

17 of the images were incorrect estimations (7 for Test, 10 for Train). It has been observed that 7 of the 10 incorrectly estimated images in the train set are actually.

Table 6 The total amount of correct and false estimations according to the dataset

Iteem	Train			Test		
	Correct	False	Accuracy (%)	Correct	False	Accuracy (%)
Hereford (heads)	237	3	98.75	58	2	96.67
Simmental (heads)	233	7	97.08	55	5	91.67
Overall	**470**	**10**	**97.92**	**113**	**7**	**94.17**

Table 7 Variances and differences between means of the digitized images according to breeds

Item	Varian	Mean (std. err)	
Simmental	0.111	0.594 (±0.005)	**Sig.**
Hereford	0.090	0.631 (±0.001)	**0.000**

Table 8 The probabilities of expected output according to the dataset (images not shown in the Table have a probability greater than %99)

No	Obs.	Prob. (%)	Exp.	Data	Res.	No	Obs.	Prob. (%)	Exp.	Data	Res.
18	H	27.49	S	Train	**X**	**380**	S	38.38	H	Train	**X**
56	H	37.70	S	Train	**X**	**388**	S	57.52	S	Train	✓
75	H	44.28	S	Train	**X**	**414**	S	67.38	S	Train	✓
92	H	65.48	H	Train	✓	**483**	S	74.81	S	Train	✓
135	H	82.04	H	Train	✓	**493**	S	89.36	S	Train	✓
181	H	93.83	H	Train	✓	**517**	S	84.46	S	Train	✓
211	H	75,05	H	Train	✓	**526**	S	94.38	S	Train	✓
229	H	98.72	H	Train	✓	**531**	S	86.23	S	Train	✓
244*	H	43.31	S	Test	**X**	**538**	S	97.47	S	Train	✓
254*	H	45.89	S	Test	**X**	**545**	S	34.99	H	Test	**X**
280	H	69.59	H	Test	✓	**558***	S	41.10	H	Test	**X**
298	H	81.30	H	Test	✓	**567***	S	43.66	H	Test	**X**
309	S	26.80	H	Train	**X**	**574***	S	46.62	H	Test	**X**
319	S	28.55	H	Train	**X**	**581***	S	48.80	H	Test	**X**
321	S	32.13	H	Train	**X**	**587**	S	60.43	S	Test	✓
332	S	33.80	H	Train	**X**	**591**	S	77.58	S	Test	✓
343	S	33.99	H	Train	**X**	**596**	S	87.59	S	Test	✓
372	S	37.90	H	Train	**X**						

* Images have a probability between 40-50%.

Obs: observed; Prob: probability; Exp: expected; Res: result; H: Hereford; S: Simmental; ✓: true and X: incorrect.

Simmental and 3 are Hereford. In the test group, on the other hand, it was observed that 5 of those false predictions were Simmental and 2 were Hereford. The images belonging to incorrectly predicted individuals are given in Figure 7.

Okura *et al.* (2019) reports an accuracy 84.2% in their study of cattle identification via score-level fusion technique, Zhao and He (2013) 93.33% via CNN from side-view images, Kumar *et al.* (2017) 95.62% from face images with salient sets of features via supported vector machine (SVM), Salau *et al.* (2014) reports that they found the determination coefficient as R2=0.70 in case of estimation body condition score (BCS) with the dataset size of 540 pictures in a high automation level. Martins *et al.* (2020) proposed the sensor of 3D LiDAR a precision level of automation gives R2=0.89 (RMSE=49.20 kg) in statistical analyses of morphological traits for lateral perspective views from 55 cattle in case of estimation of live weight.

Smart precision farming technologies have been fast improving the cost-effectiveness, safety and sustainability of massive animal production through the analysis, processing, obtaining and application of information in terms of animal productivity and welfare. Although the measuring of weight via sensors constitutes a non-invasive system, it is still influenced by many factors in the case of farm conditions like irregular lighting and cattle in motion. Therefore, accurate weight estimation needs to fit the farm-based requirements and stability of work by maximizing precision and repeatability for a long time. Moreover, the measuring and estimation BCS based on image recognition and other related techniques show significant development. Despite increasing interest in tracking by 2D and 3D sensors in livestock, they are still having a higher cost than the estimation over images, and it has also to be noted how to generate a method of extracting various kinds of traits from the videos of moving cattle.

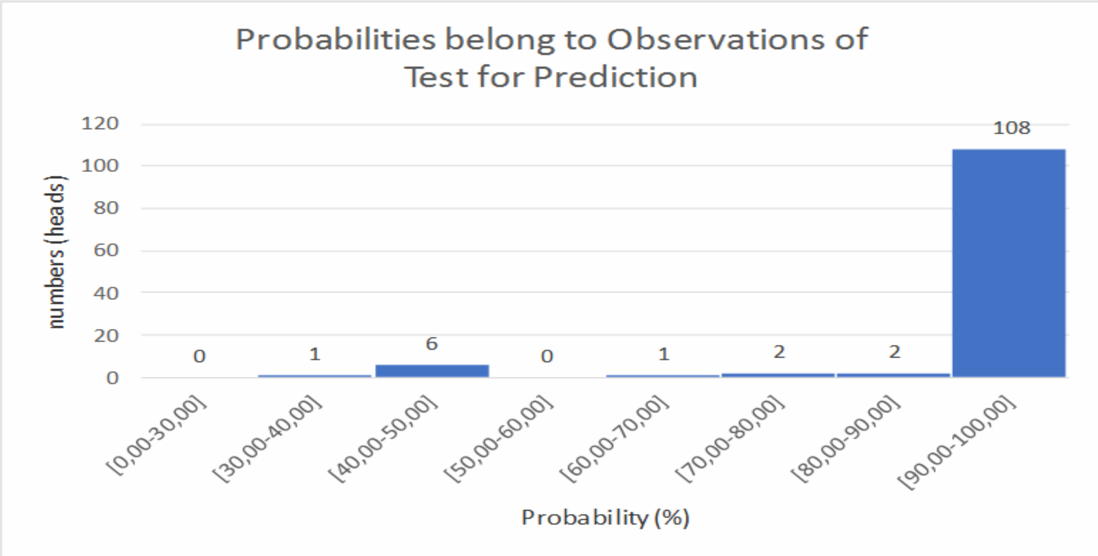

Figure 6 The histogram shows the probabilities of observations belonging to the test

Figure 7 False predictions

Additionally, classical electronic tagging-based approaches like RFID can show up to 100% accuracy in case of identification. But the disadvantages belong to its high-cost prices and other reasons such as the difficulties in use (e.g., manually tagging) and even be harmful to the animal making producers avoid from techniques of classical electronics. Even if RFID provides advantages, has some security and privacy call-outs which bring any system sensitive to numerous risks besides challenges in manual tagging and being injurious to the animal. Other widespread technological instruments, on the other hand, are visual and biometric feature-based approaches. Despite these approaches showing an accuracy between 84-98.33%, they have still some problems in themselves like lack of applicability due to the difficulties in capturing iris and retinal pictures from animals in action (Qiao *et al*. 2021).

Summing all up, different methods are used in tracking and recognition of animals, e.g., individual identification via ear tag-based approaches, retinal-iris, facial or coat and muzzle pattern based visual identification techniques; breed classification, body condition score and live weight estimations etc.

Considering that each system has its own shortcomings, it would be a more accurate approach to try to determine the enterprise-based optimal and most suitable option by evaluating the advantages and disadvantages of the instruments rather than deciding the best one. Some advantages of the image processing method presented in current research, e.g., its low cost and labor requirement, high accuracy, ease to use, and low processor load while execution of analyses makes it more attractive.

CONCLUSION

These results show that FCNN which is a ML method and also used for image classification in the determination of cattle breeds, will give successful results. Considering the increased workload due to the rapidly increasing animal presence and data volume, and the increasing level of mechanization and automation as a result of the requirements of industrial livestock in our age, further research on individual identification, determination of age, body condition score, image recognition and classification with machine learning required. Different results will be obtained from the models established with various artificial networks such as convolutional neural networks. Therefore, using FCNN in livestock in terms of breed classification, individual identification, determination of age and body condition score via image recognition and classification will give beneficial results thanks to its advantages in low processor load and high accuracy rate. More successful results can be obtained with a larger dataset. The difficulties created by such a large data flow in data recording, tracking, analysis and synthesis in herd management increase the need for robotic systems.

ACKNOWLEDGEMENT

This research has been conducted in the scope of "The Technological Aplications in Livestock" project at Cukurova University in Adana/Türkiye, Agricultural Faculty Department of Animal Science, Large Ruminants' Laboratory.

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