Digital Goat Farmer's Assistant – Using Facial Recognition to Identify Goats

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Abstract

In this research we have looked at alternatives towards identification of goat identities in the goat farming industry. The goat farming industry currently uses earmarks to identify goats, however the combination of strict new legislation towards goat identification and the effect earmarks have on animal welfare has the industry longing for a new solution to goat identification. In this paper we explain how we created goat face recognition with a supervised learning neural network to identify twelve individual goats. The research resulted in a 83,33% predicted accuracy, suggesting that goat identification is feasible.

Authors Keywords

Livestock agriculture; computer vision; animal identification; machine learning; livestock monitoring.

1. Introduction

In livestock agriculture, earmarks are widely used to identify individual animals. Goat farmers are legally obligated to attach two earmarks to the goats' ears within the first six months of their lives. These earmarks have embedded identification numbers, which are used to report the goats' residence and migration information to the Dutch government's *"Identificatie & Registratiesysteem (I&R)"* (RVO, n.d.). The registration is mandatory to guarantee food safety. However, the system of earmarks is not without flaws. Our interview with a Dutch goat farmer established that he has to replace a fourth of all earmarks annually.

Aside from fast degradation, earmarks can cause health problems in goats, including inflammations and permanent deafness (Minister van Landbouw, 2009; van Es, 2014). As a result, there are several biological farmers who do not want to use earmarks, reasoning that it causes animal suffering (Schuiling et al., 2004; van Es, 2014). Finally, a 2019 regulation enacted by the Dutch government (Ministerie van Landbouw, Natuur en Voedselkwaliteit, 2018) warrants a €1500 fine for every defective earmark. Therefore, costs of the earmarks would increase even more significantly ("I&R wordt strenger | Geitenhouderij", 2019). An alternative to the earmark is the use of an injected RIFD-chip (Voulodimos,

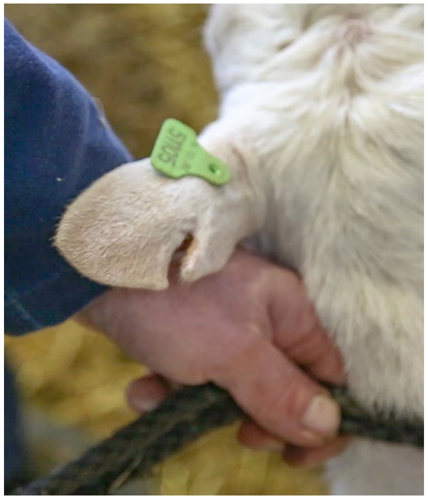

Figure 1: *A close-up of a generic goat's earmark. In this photograph, we can see that the goat's ear has been damaged as a result of an earmark tearing out.*

Patrikakis, Sideridis, Ntafisb & Xylouri, 2010). Similar to the earmark, this chip can be scanned, yet it does not degrade over time, and does not harm the goat in any way. However, an interview with a representative of agricultural automation company Elda informed us that the use of chips as an identification system for goats is not recognised by the Dutch government, which makes them not allowed. ("Toegestane merken en combinaties", 2010)

Personal information of a goat including birth and medication are saved in personal files. Every time a farmer needs to adjust a goat's individual file, they are required to locate and catch the goat. This can be a difficult and physical task: the target is surrounded by dozens of goats, and the animals are not always cooperative. After the goat has been caught, the farmer needs to manually scan its earmark. Similar difficulties are encountered when a specific goat needs to be located. Usually, only the identity number and its pen are known, meaning that the farmer scans multiple goats in order to see which one is the goat of interest.

In conclusion, there are several problems surrounding the earmarking of goats. A part of the problem focuses on the animal welfare. Next to this, the business standard proves to be time- and labour-intensive. Lastly, the regulations for goat identification are sharpened, meaning that the farmer is in risk of receiving costly fines. However, there is no alternative that is easily accessible. In this report we explore the viability of the *Digital Goat Farmer's Aid (DGFA)*, a computer vision-based goat identification as an alternative to earmarks. We discuss the technology required to operate such a system, and examine the automation opportunities created by this system. Finally, we discuss how our findings contribute to the possible integration of goat recognition within the current goat farming industry.

2. Related Work

One of the first studies contributing to the development of image recognition was the development of pattern recognition systems in 1960 (Andreopoulos & Tsotos, 2013). In 1973 the first fully automated image-based machine was created. Following was a series of products that were developed for several industries like biomedical research, food industry (food recognition), electronics and machine industry, and for functions like traffic monitoring, license plate recognition, and monetary bill recognition (Andreopoulos et al., 2013).

Another important step in image recognition was an invention from 2001, the Viola-Jones detection algorithm, better known as the first face detection algorithm (Viola & Jones, 2003). Later, image recognition received some adoption in commercial systems, seen in the Google Goggles and in mobile product recognition systems for smartphones (Branscombe, 2010; Tsai et al., 2010). Currently, additional to such algorithms, machine learning is used for image recognition. A recent study by He, Zhang, Ren, and Sun (2016) shows how it is possible to use deep residual learning. This is relevant for our project as it proves that it is possible to teach a system to identify what object can be considered a goat.

Several studies have been conducted on cattle with regard to identity recognition. For example, Abdelhady, Hassanenin, and Fahmy (2018) have created a dataset to perform sheep identity recognition. For every sheep, they created an image of the two sides of the face, and one image of the teeth. Similarly, Kumar, Tiwari, and Singh (2016) created a dataset with images of cows. They also attempted to perform face recognition, and concluded that this is feasible for such a dataset. A prerequisite for such a success is that it is important to keep the illumination, pose, and image quality

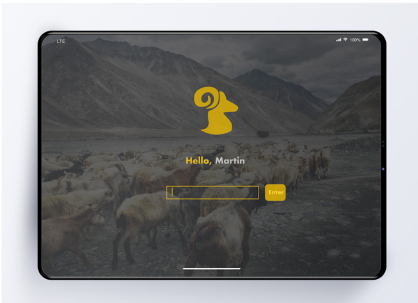

Figure 2: *Log-in screen of the DGFA.*

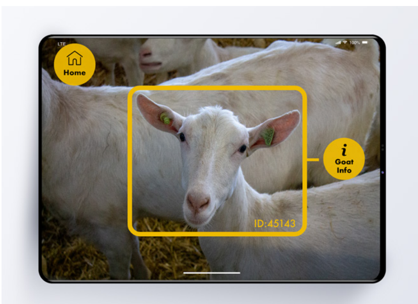

Figure 3: *Goat identification user interface.*

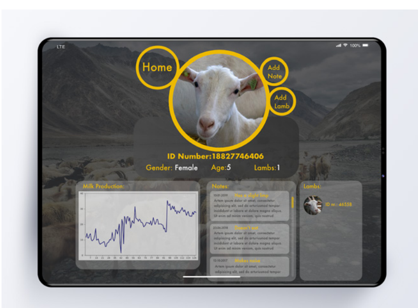

Figure 4: *Detailed information on goats is displayed at an individual level.*

as similar as possible (Kumar et al., 2016). Furthermore, the background should be stable, which helps for segmentation and background subtraction (Abdelhady et al., 2018).

Currently, a partnership has been created between the agricultural company Cargill and the machine-vision company Cainthus, who want to use the identification of cows to detect odd behavior to, in the long end, prevent animal loss (Loesch, 2018). Loesch (2018) also mentions that in the long run, the system should expand to other species, like swine, poultry and aqua animals. As it is not yet found whether face recognition would be possible for goats, we see this as our addition to current existing research. Besides this, we also see an opportunity in creating a user friendly interface, as the system developed by Cargill and Cainthus does not seem to put emphasis on this (“Combining machine vision and”, n.d.).

3. Concept Overview

With the *Digital Goat Farmer’s Aid (DGFA)*, we aim to create an animal-friendly alternative to earmarking. This novel system based on computer vision allows for identification of goats based on their facial features. A portable phone- or tablet equipped with a camera can be used to scan- and identify goats. The integrated user interface supplies the farmer with relevant information about the goat, including health records, milk production and manual notes added by the farmer.

In order for the *DGFA* to work in current goat farms, both software and hardware implementations are needed. The recognition algorithm needs a database of facial photographs to recognize individual goats, hence an automated camera system should be integrated. For this, the milking carousel is envisioned to work well: goats are led to this place multiple times per day, and the restrained position allows for photos to be taken from consistent angles. Additionally, the habitual use of the system allows for automatic adjustments to be made to the dataset, such as adjustments in appearance, or inclusion of new goats.

The user interface of the *DGFA* creates a visual overview of the herd’s status. Features of the interface include goats identification, goat search, a detailed database with information about the complete herd, an agenda and quick overview of lambing- and sick goats. The simple and detailed overview of the app allows the farmer to stay informed about his herd and quickly notice when something is wrong. In conclusion, the *DGFA* is envisioned to be an informative powerhouse, assisting the farmer in managing their farm at a glance.

Figure 5: *The centralized dashboard allows access to all functionalities.*

Figure 6: *An impression of the data gathering process in the milk carroussel. A consistent viewing angle is achieved by the use of a tripod.*

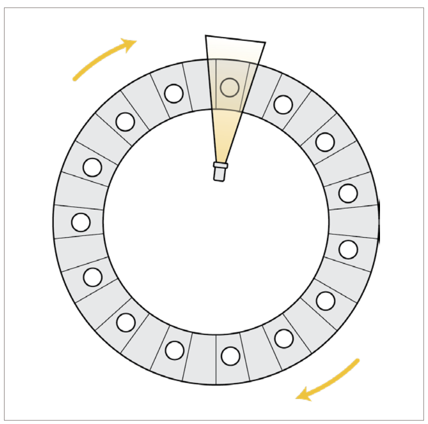

Figure 7: *Schematic top-view of the data gathering setup. After the sequence of photos is taken, the carroussel rotates a set amount of degrees, allowing the next goat to be photographed.*

4. Technical Realization

To create a goat identification system, a normalized dataset of facial pictures of goats is required. As such a dataset is not publicly available, we created a dataset of goats ourselves. This dataset was preprocessed, after which features were extracted. This processed data was used in a neural network to train a goat identification system.

4.1 Data Gathering

50 to 70 photos were taken of 24 randomly selected goats while they were positioned in a milking carousel (see Figures 6 and 7). The carousel can rotate in a set amount of degrees, therefore we could fix the location of the camera by placing it on a tripod. This ensured that the goats pictured would be in the exact same location over and over again, however, every goat would stand in a different slot of the carousel.

4.2 Data Preprocessing

From the 50-70 photos taken of the 24 goats, we have created a set of five training-photos and two test-photos for twelve goats. Selection of the goats was not performed randomly, as we included goats with different fur colors and features like the presence of horns and a goatee. After selecting the photos for our dataset, we standardized every photo by adjusting the white balance to the absolute white sticker located in every slot. During the data gathering process, identical white stickers were positioned next to each goat.

By using Adobe Lightroom, this reference point was selected to standardize the white balance in colour temperature and green-magenta shift. Subsequently, we manually cropped the images to minimize background information, so that relevant information about the goat was preserved. A more elaborate method of foreground extraction has also been considered and tested. However, this was without success and is discussed in Section 6. The final step of our preprocessing was downscaling the images to 100x100 pixels, which reduced the amount of input features entered in the neural network and therefore ensured a faster processing speed. These dimensions were chosen based on best practices derived from literature and professional tools (Cunningham, Nusseck, Wallraven & Bülthoff, 2014; Marciniak, Chmielewska, Weychan, Parzych & Dabrowski, 2015; Kairos, 2017).

4.3 Feature Extraction

We are able to distinguish image processing methods for goats into two different types: the type of fur, and the shape of the head. When looking at the type of fur we are able to extract information about the colours in the fur and differences in intensity. When looking at the shape of a goat's head we were mainly focused on the difference in outer boundaries of their head, assuming that they would differ from goat to goat.

For every feature extraction method, we created a Matlab code. The codes for the train- and test data can be found correspondingly in Appendix A. For both datasets, the code first loads the data, after which it performs several feature extraction methods. In the end, it outputs the data to a .csv file.

Type of fur

Multiple Multiple methods for extracting the features of the fur were considered, for which we made use of RGB, HSL and black/white-intensity data. We started with extracting the redness, greenness, and blueness (RGB) of every pixel in the image. Consequently, we calculated the average RGB values

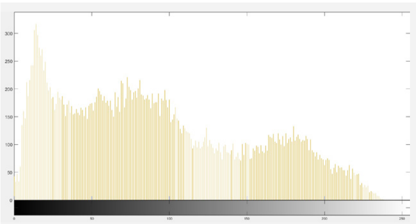

Figure 10: A histogram visualising black/white-intensity values of a photograph taken of a goat.

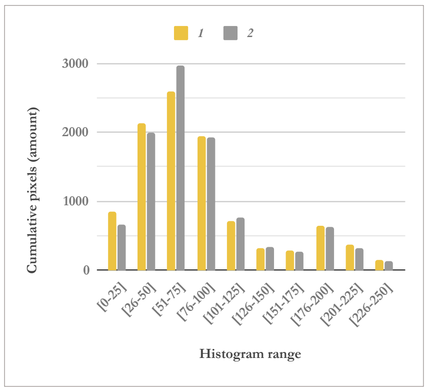

Figure 11: Comparison of histogram intensity levels of two goats: the cumulative pixels in the ten intensity ranges are displayed.

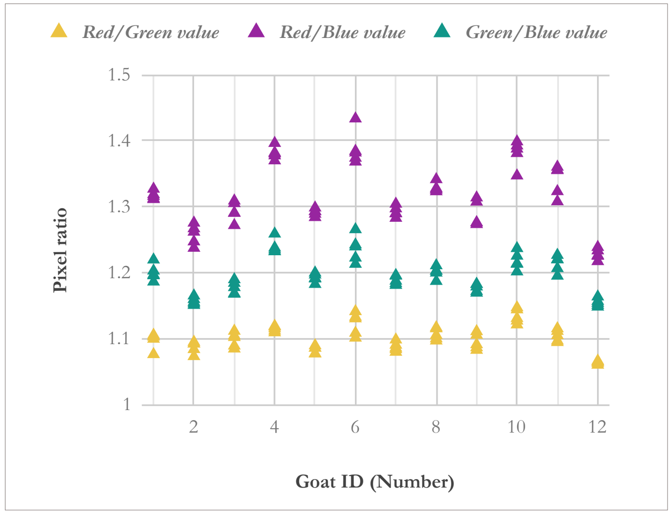

Figure 8: Scatterplot of RGB pixel ratios for twelve goats.

for every image, which resulted in three variables. Despite the fact that intuitively the RGB values seemed to be proper values to include in the neural network, we also looked at the ratios between these values. As can be found in Figure 8, the difference in ratio values is rather small, so eventually we did not expect the RGB values to be suitable for the neural network to compare the goats.

Another method of extracting information of coloured images, is looking at the hue, saturation, and luminance (HSL). As can be seen in Appendix A, we calculated the HSL values per pixel. Afterwards, we calculated the average HSL values, which resulted in three variables per image. Looking at the output data in Figure 9, we can intuitively see that this dataset would potentially be a good dataset to distinguish goats, as the values are quite different per goat. Next to looking at coloured images, we extracted black/

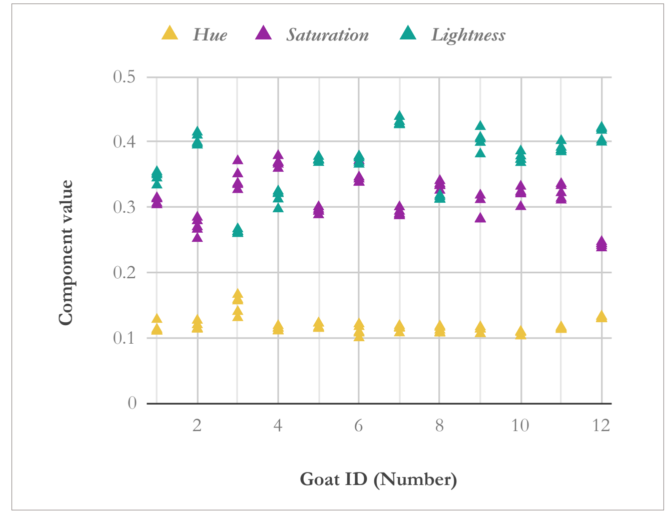

Figure 9: Scatterplot of HSL value distributions for twelve goats.

white-intensity data from grayscale images. We did this by calculating the amount of pixels per intensity level. This data can be visualized in a histogram. An example of such a histogram can be found in Figure 10. For this data we calculated the total amount of pixels per 25 intensity levels, which resulted in ten variables. In Figure 11 the corresponding graph can be found. Based on this graph we expected the black/white-intensity data to be good input for our neural network.

Shape of the head

For the measurement of the shape of the head we also looked at several approaches. We collected data from edge detection, and by using foreground segmentation we could calculate several facial ratios. We have performed edge detection on grayscale images, for which we used three different types of filters: *Prewitt*, *Sobel*, and *Canny* (Maini & Aggarwal,

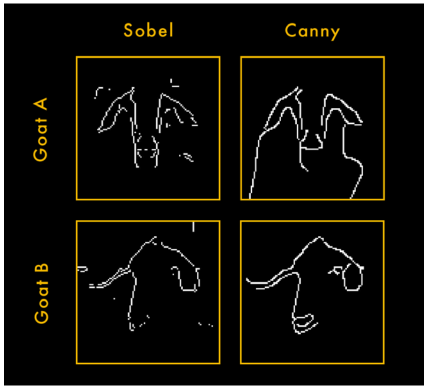

Figure 12: *A comparison of Sobel and Canny edge detection filters for two goats.*

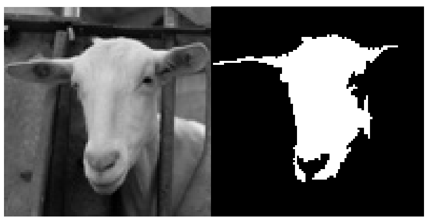

Figure 14: *Before- and after-view of the foreground segmentation procedure.*

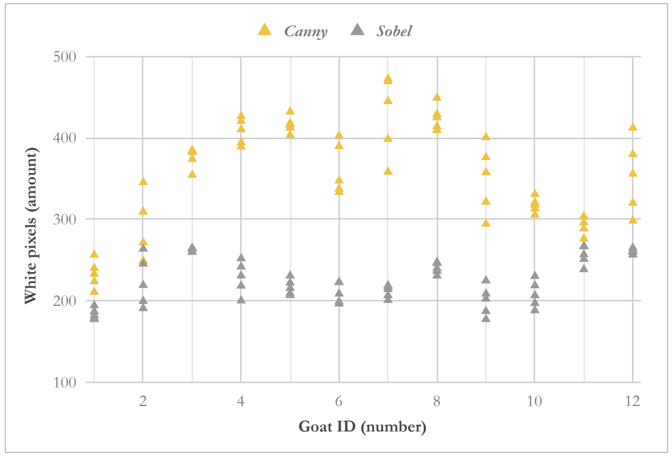

Figure 13: *Scatterplot illustrating the variance in white pixels of both filters.*

2009). For every filter type we tried to find the best threshold, so we would include enough information about the goat, thereby trying to minimise the background information. We found that the Prewitt filter did not give accurate results, but comparing the other two filters we found that the Canny filter performed better for one goat, but Sobel filter for yet another goat (see Figure 12). This is why we decided to include both Canny filters and Sobel filters data. The output images of the edge detection included only black and white pixels, which is why we consequently calculated the amount of white pixels per image. In Figure 13 the amount of white pixels per image per goat can be found, which indicated that the Canny data would be more relevant for our neural network compared to the Sobel data, as the variance between individual goats is greater.

In addition to edge detection, we also extracted data based on foreground segmentation. Performing foreground segmentation on the images resulted in a new image

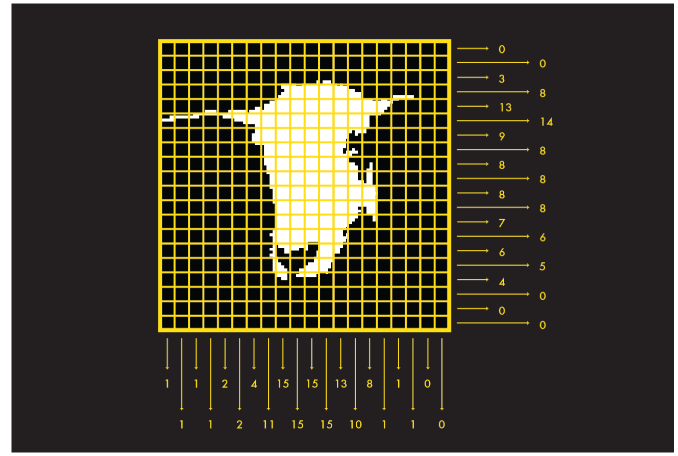

Figure 15: *Visualisation of pixel amounts calculated for rows and columns. For simplicity's sake, a 20x20 grid is shown in this figure, however a 100x100 grid was used as input for the neural network.*

including only black and white pixels as shown in Figure 14. For this image we calculated the total amount of white pixels per row and column (Figure 15), which resulted in two arrays each containing 100 variables. With these arrays we could perform two different analyses; length and width ratio of the head, and vertical and horizontal ratio of pixels.

To determine the maximum length and width of the head we looked at the maximum number within the arrays. The maximum values gave us the relative measurements of that particular goat's head. Using this data we could calculate the ratio between length and width of the head, allowing us to look at the head dimensions without being limited by the relative distance to the camera. Next to the ratio between length and width of the head, we have looked at the center point in which the widest and longest part of the goats head cross and compared these locations with the maximum length and width of the head. We divided the vertical Y value with the total width of the head and the horizontal X value with the total length of the head. This way the shape of the head can be better determined. For example, if a goat has a very wide part of the skull on the top of his head the ratio will differ from a goat with a wide part of the skull around the eyes.

By dividing the vertical pixel array by the horizontal arrays we created another array which contained the ratio between the vertical and horizontal pixels. This data contains much more detail about the shape of the head compared to the length and width ratio of the head.

4.4 Neural Network

After we had obtained the feature extraction data we uploaded it to Neuroph Studio. In Neuroph Studio, we created a multilayer perceptron neural network, with as input variables the HSL values, the black/white-intensity data, the edge detection data (Canny filter), length width ratio of the head and vertical and horizontal ratio of pixels (Gardner & Dorling, 1998). We tried several combinations of these variables in our network, to see which combinations would result in the best goat identification. During the search for the right features we trained our neural network with different data points, during all this we looked closely at the predicted accuracy provided by the test set.

Prediction accuracy of a neural network is strongly affected by a couple of variables (Gardner et al., 1998; Tian, Zhang & Morris, 2002). Firstly the network structure needs to be appropriate for the amount of input data that enters the network. The amount of hidden neurons is dependent on the amount of input variables, as the amount of hidden neurons always needs to exceed the amount of input features. Secondly the type of learning technique used by the neural network can influence the predicted accuracy. When one of the above named variables is not fitted to the type of data, the amount of data or the learning goal, over- or underfitting can occur. Underfitting usually occurs when the network is not able to train the data well. Causes for this can be an inappropriate network structure with too many or too few hidden neurons, not enough training iterations, or incorrect weights between the neurons. Overfitting is when training of the data has gone well, but the networks underperforms when confronted with never seen data. Overfitting usually occurs when the network structure is too large, has had too many training iterations, incorrect weights between the different neurons or an insubstantial amount of training data.

In our case we used supervised learning as learning technique for our neural networking, training with a labelled training dataset. During the testing of the features we made sure that the hidden neurons in our hidden layer always exceeded the amount of variables inputted in the network. Training iterations varied between 250 to 25.000 iterations, dependent on the different input features. Robustness of the network was tested by running a test dataset through the network, by doing so we received a predicted accuracy for the identification of our twelve goats.

5. Results

To allow the *DGFA* to identify goats, we need a neural network that identifies the goats as accurate as possible. To achieve this, we created a substantial dataset of variables mentioned in Section 4.4, for which we found the optimal combination of variables for our multilayer perceptron neural network. We found that when implementing the HSL values, the black/white-intensity data, the Canny edge detection data,

Input variables	Predicted test set accuracy
HSL values + Horizontal pixel values	41.67%
HSL values + Horizontal/20 pixel values	37.50%
HSL values + Horizontal/20 pixel values + Vertical/20 pixel values	75.00%
HSL values	79.17%
Histogram + Edge detection (Canny)	66.67%
HSL values + Vertical and horizontal pixel ratio	44.83%
HSL values + Length & Width head ratio	75.00%
HSL values + Black/white-intensity + Edge detection (Canny) + Length and width head ratio	79.17%
HSL values + Black/white-intensity + Edge detection (Canny) + Vertical and horizontal pixel ratio	83.33%

Table 1: *The neural network's performance across combinations of input variables.*

and vertical and horizontal pixel ratio, the most accurate goat identification could be performed. This combination had an error-rate of 0,2% in the training dataset, and correctly identified the goats of the test-data 83,3% of the time. In Table 1 the predicted test set accuracy for the implementation of other combinations of variables in the neural network are shown.

6. Discussion

6.1 Approach

Preprocessing

As mentioned in Section 4.2, we have attempted to perform foreground extraction, which means that we wanted to have an image containing only the relevant information of the goat, excluding all background noise. Foreground segmentation can be performed by subtracting the background image from the image including the foreground, where the foreground should then be the resulting image (Agrawal, Shriwastava, & Limaye, 2010). However, this was unsuccessful, as our images were not perfectly aligned with each other.

Apparently we had not created a stable enough background, as was suggested by Abdelhady et al. (2018). Because of this, information was subtracted on wrong positions, which did not result in the desired foreground image. In future research a fixed position on the carousel itself, instead of a tripod in front of the carousel, may improve the results of the foreground segmentation. By positioning the camera onto the carousel the relative position of the goat's surroundings to the position of the camera does not change. Therefore the background of the carousel within the picture will not differ. While looking at our feature extraction data, we can see a some noise which is caused by the background. This has had a very big impact on our results.

Head position during data gathering

Despite the fact that the goats were not able to move their Despite the fact that the goats were not able to move their body during data gathering, they were able to move their heads. During the photo session we encouraged different head positions, we thought this would help the identification of each goat from different angles. However, this turned out to be a deficit to our dataset, as head position turned out to be a big influence in distinguishing the shape of the goats head. Not only because the head angle influenced the different facial features that would be pictured, but also because the shadowing on the fur changed the fur color.

Alteration of the dataset to front facing pictures showed an increase of 5% accuracy in identification of the goats. For this reason, we decided to only include the frontal head positions, which unfortunately means that our final prototype is not generalizable to other head positions. As a solution to this, different head angles of a single goat could be labeled separately. This way the neural network only compares pictures with the same head angle, eliminating problems with fur color and shadow.

Neural network

When we used the HSL values, and the vertical and horizontal pixel ratio for the neural network, we experienced overfitting. In this case we had an input of 103 variables with one hidden layer and an amount of hidden neurons exceeding the amount of input variables. The structure of the neural network was balanced and training of the training dataset was done within 250 iterations displaying an error-rate of 0,16%. However, when testing the network with the test dataset we only had a predicted accuracy of 44,83%, which indicated that the neural network was well trained on the training set. However, it could not distinguish the differences in the "unseen" test data, therefore we concluded that the network was overfitted. We believe the minimal size of our training dataset was the cause for the overfitting. The neural network was able to train very well and quick, but the minimal size of our training set meant that the test data was to different form the training set.

With a larger training set more different pictures of one goat, the training set would allow the neural network to recognise the goat better. Thus meaning that the differences between training and test data would be minimized, creating a higher predicted accuracy with the test data. Therefore we advise future research to be done with a far bigger dataset. Another option to avoid this problem is adding other input features, this way a particular goat can be identified by the use of more specific head features. After adding the black/white-intensity data and the Canny edge detection data, the neural network was able to train very well and quick again and showed an increase of 38,5% accuracy.

Feature extraction

Apart from the feature extraction methods explained and used in Section 4.3, we have implemented several other methods. As well as explaining the methods, we will give an explanation on why they were unsuccessful, and whether we think they should still be considered in future work.

Our first attempt in feature extraction started with looking at the RGB values in a colour image. The extracted average RGB values looked very different at first, but when we applied this data into the neural network it did not converge. To identify goats, the neural network will compare the different values. For example, the red values from goat 1 may differ from the red values from goat 2, but if the green and blue values differ with the same ratio, the neural network is not going to detect a difference. After looking into this we found another way of extracting color features by using HSL values.

The Canny and Sobel edge detection showed us relevant data, however we only looked at the amount of edge pixels, which heavily reduced the data resolution. We have not looked deeper into how we could best comprise this data to the right amount of variables. This could thus be something to consider when improving our identification system.

6.2 Future Work

Preprocessing the data

During the preprocessing stage we have performed all steps manually. A big improvement can thus be made concerning the automatisation of the process. First of all, the white balance was adjusted for every image using Adobe Lightroom. The white sticker was manually targeted as a reference point for 'true' white. The more sophisticated *X-Rite ColorChecker* card can be used to correct colours beyond white balance. By using Kordecki, Andrzej & Palus' (2014) framework, this card can be detected for automatic correction of colours.

Then, the cropping could be performed based on the automatic detection of features of the goats. This automatic detection could for example be performed by locating the four boundary pixels of the goat using foreground segmentation. Around these boundary pixels a square could be placed that makes sure all the relevant goat information is included. Consequently, downscaling to 100x100 pixels could be easily automated as well in Matlab (Mathworks, 2018).

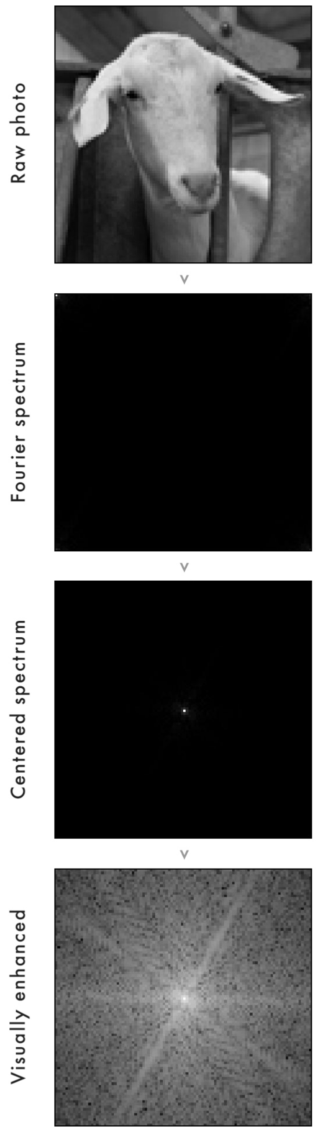

Figure 16: *A visual overview of the Fourier transformation sequence.*

Feature extraction methods

An additional method to extract relevant data out of the images of the goats could be to perform Fourier analysis. With this method, an image becomes decomposed into its sine and cosine components, after which an output image shows the frequency domain of the input image (see Figure 16) (Ell & Sangwine, 2007). As we do think the resulting output, which is a matrix of frequencies contained in the spatial domain, could be of use, we have not deepened into how we could best comprise this data into fewer variables. This could thus be something to consider when improving our identification system.

Future Implementation in the Industry

This research shows that facial identification of goats is possible and certainly feasible within the near future. Thereby solving all previous indicated problems associated with the current earmarks and enabling the possibility of a smarter way of farming. The previously introduced features of the *DGFA* are a first step in developing a goat farm that is more efficient, humane and environmentally responsible. The functionality of the system can be extended by establishing connections with external sources. The milk manufacturer produces rich data on milk production and composition, which can be linked with additional cameras in the barn to gain insights in the effects of living environment on milk production- and quality (Goetsch, 2011).

A step beyond identifying individual goats would be to learn from both individual- and group goat behaviour. Anomalies in behaviour can be detected, and offer the potential for typical farm processes to be automated. Such as analyses of the influence upon eating behaviour and milk production of the herd, compared to the food supplement supplied to them.

The full system will be able to accommodate for every individual goat, thereby creating the perfect living environment. This will not only improve milk production, but it will also improve the quality of life of the goats and it will allow the farmer to work with more ease, and less stress. In our research proposal, however, we consider this as future work. The focal point of this project is the *DGFA's* user interface, the creation of the database and recognition of the goats.

Deep Learning

In order for the system to become embedded in the industry a far more robust method of identification needs to be used. An accuracy of 83,3% simply is not enough when a major industry depends on the correct identification of the goats. We therefore advise further research to look into the implementation of a deep learning algorithm. To be even more specific a convolutional neural network. For such an algorithm to work a far larger size dataset needs to be created combined with strong computing power (Krizhevsky, Sutskever & Hinton, 2017).

By using a convolutional neural network the learning algorithm will be able to go beyond image recognition. Instead of comparing data extracted from the picture it will be able to recognise features of a goat such as horns, eyes and goatees. When combining these features with the position on the head of a goat, the system will be able to distinguish the difference between every goat. Thus being more robust and more qualified for implementation into the field of goat farming.

7. Conclusion

During this research we have looked at how image recognition with the use of a neural network can replace ear tags as identification method for goats in the agricultural sector. We can conclude that with the use of HSL values, the black/white-intensity data, the Canny edge detection data, and the vertical and horizontal pixel ratio as input for a supervised learned multilayer perceptron neural network will result in an predicted accuracy of 83,3%. While this is not robust enough for implementation in the agricultural industry, it does show that identification of goats via image recognition is feasible. Therefore we advise further research to be done with a bigger dataset and the use of a deep learning convolution neural network.

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Appendix A: Code and Dataset

All code- and data-related files used in this research have been made publicly available in a packaged file. This file includes:

— *Pre-processed photos of goats, used in the neural network;*

— *Matlab code of the feature extraction procedure;*

— *CSV files of the final test- and train data*.

For access, please follow the URL below:

https://tinyurl.com/ycsn8rcj

Appendix B: Concept Video

A concept video was made to better illustrate the context of this project. This video can be found online by following the URL below:

https://youtu.be/XMCSCFGmgu8