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Master thesis Applied Data Science

Assessment of the Coat Colour Phenotype of the Original Dutch Landrace goat, using a Machine Learning approach

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Abstract

The Dutch Landrace goat (Nederlandse Landgeit in Dutch) is a goat species that has lived in the Netherlands since the 17th century. From around 1906 until 1910 goat farmers cross-bred the original Dutch Landrace goat with other goat species, causing the original genes to be lost. In this paper, a data pipeline is designed to assess the coat colour phenotype of the original Dutch Landrace goat from old paintings. This is done to answer the research questions: *What colour(s) does the coat of the Dutch Landrace goat consist of?* and *What pattern(s) does the coat of the Dutch Landrace goat consist of?*

This research has shown that the colours black, brown and white occur in respectively 33,3%, 34,4% and 63,4% of goats. The three most common colour combinations are ’white’, ’brown and white’ and ’black and white’. Regarding coat patterns, it has been found that 58,3% of all observed goats contain one of four reoccurring patterns. These patterns are ’completely white’ (32,0%), ’dorsal stripe’ (13,3%), ’completely brown’ (9,3%) and ’black head with white body’ (4,0%).

These findings give goat breeders consensus about the historic appearance of the Dutch Landrace goat, so breeding standards can be formed to which can be bred. Additionally, although a limited amount of data could be used, the results of this research and the database that has been constructed could form a basis for further research.

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Contents

1. Introduction

This chapter first gives context and an explanation for the research question. Thereafter, the goal of this research and the research questions are formulated.

1.1 Background and context

The Dutch Landrace goat (Nederlandse Landgeit in Dutch) is a goat species that has lived in the Netherlands since the 17th century [1]. During this time, the population fluctuated and to improve milk production, from around 1906 until 1910 goat farmers cross-bred the original Dutch Landrace goat with several different species (Saanen and Toggenburg goats), first from Switzerland and later on from Germany as well [2]. Due to crossing the Dutch Landrace goat with different breeds, the original Dutch Landrace goat and its genes have been lost.

The national breeders association of Dutch Landrace goats (Landelijke Fokkersclub Nederlandse Landgeiten), from now on LFNL, try to preserve the goat race and breed goats with similar phenotypes[1] as the original goat. Except for cloning, it is biologically impossible to obtain living goats with the exact same DNA, corresponding to the Dutch Landrace goat from before the twentieth century [3]. To get as close as possible, breeders of the LFNL try to match the phenotypes by back-breeding, a form of selective breeding. In selective breeding, specific characteristics are developed by selecting specific animals with these characteristics to reproduce. Back-breeding does this with phenotypes of ancestors of an animal species.

Since the photo camera only became available to the mass market at the beginning of the twentieth century, there are no high-quality photographs

[1] all observable properties of an organism

of the Dutch Landrace goat. Because of this, the reference for goat breeders exists merely of artistic representations of the goat, like paintings, drawings and sculptures. This lack of sources results in the fact that there is no clear consensus on what the appearance of the Dutch Landrace goat should look like, and thus a lack of breeding standards.

1.2 Formulation of research question

To provide this, the visual appearance of the Dutch Landrace goat will be established. This will be done in two partially overlapping studies. In the thesis "*Do 2D representations using Procrustes analysis accurately represent the head shape of the Dutch Landrace goat in comparison to the consensus shape?*" fellow master student Michel Doré has performed a morphological analysis about the head of the Dutch Landrace goat. In this paper, the coat colour phenotype of the original Dutch Landrace is examined from old paintings. This is done by answering the following research questions:

1. What *colour(s)* does the coat of the Dutch Landrace goat consist of?
   1.1 How is this distributed?
2. What *pattern(s)* does the coat of the Dutch Landrace goat consist of?
   2.1 How is this distributed?

By answering these questions, clarity is given about both the colour distribution and combinations, and the pattern distribution and combinations of the Dutch Landrace goat.

2. Literature Review

In this chapter, literature relevant to fundamental concepts in this research is reviewed. First is discussed what effect colours in paintings can have, and what can influence the perception of colour in paintings. Then determining factors of goat coat colours are explained. And finally, the cause of patterns and common patterns in goat coats are described.

2.1 Colour in paintings

As mentioned in chapter 1, artworks like paintings, drawings and statues (all of considerable age) are the only source of information regarding the colours and the patterns of the coat of the Dutch Landrace goat. Because of this, several things must be taken into account. First of all, throughout the centuries, painting techniques have changed and improved. This had to do with better insights, but also available materials. After 1800, increased international trade made the arrival of new materials as for example different pigments possible (such as different shades of yellow and blue), which enlarged the available colour options [4]. As a consequence, opportunities increased and there was room for paintings to get more lavish.

Secondly, paintings and drawings are artworks. Depending on the artist and its style, the piece of art can differ in the degree to which it is realistic. When information needs to be extracted from paintings, it is important to know the differences in style, so incorrect information can be recognised. Abstract paintings, for example, can look far from their original inspiration. Often to such a degree, that the inspiration can not be recognised anymore. With expressionism, images can look distorted, sometimes caused by unrealistic colours. A style more truthful to reality is realism. Here, drawings are intended to look realistic in the eye of the viewer. But in reality, the painting does not have to be a representation of something real. An artist can still implement their own style and likings. These different styles will as a result give, unlike photographs, different paintings. Even if different artists would paint the same object or scene. So, this will have an influence on the perception of that what is painted.

This brings us to the next topic. Different styles are not the only way paintings can look different from reality. When taking a closer look at a painting, it can be noticed that all sorts of artistic tricks can be implemented to create illusions. In 1976 Birren stated the following about these illusions, which he called 'Perceptionism': "It continues beyond the eye, up the optic nerve into the brain. It is less concerned with what the eye sees literally than with the way in which the brain interprets what is seen." [5]. This applies for example to illumination, where consciously knowing an object is in the shadow affects the way the viewer perceives that object. A famous example of this effect is the Checkershadow illusion, by Edward Adelson [6]. Besides, neighbouring colours have a substantial effect on the colour hues of those adjacent colours [7]. But Perceptionism also affects the way colours are composed. Over a maximum of forty thousand different perceptible colours are estimated to be in an oil painting [8]. Together, on a small scale, all these different colours form only a few different colours that are consciously perceived in the human eye. All these methods are used in paintings to give them a certain effect, like illusions of depth, perspective and light and dark for example.

Finally, colours in oil paintings tend to change and lose their intensity because of illumination, moisture and temperature changes [9]. This results in less accurate and reliable colour values with older paintings.

2.2 Coat colours in goats

The colour of the coat in goats is caused by pigment cells in the epidermis (the outermost layer of the skin) that generate melanin, which gives the hairs their colours [10]. Which colour depends on the genes it gets from its parents. These genes are found in the chromosomes of organisms. A locus, a specific point on a chromosome where a gene is located, contains information about the pigment, and thus the phenotypical appearance of (in our case) a goat. One of the most prominent determining factors of the colour of goat coat is the Agouti locus [11]. The pigment in goats consists of two types, eumelanin and pheomelanin [12]. In 1994 Adalsteinsson mentions three pigment types in goats; two eumelanin pigment types, black and light brown, and one red, tan or cream phaeomelanin pigment type [13]. These pigment types, or a combination of them, form the coat.

When the black or light brown eumelanin pigment spreads uniformly, we respectively get a black or light brown coat. A black or brown goat with white markings is a result of a lack of pigment in those white areas. A completely white goat can occur in two ways. The first is because of a very pale pheomelanin shade, where pigment is present. The second way is when the goat is essentially completely covered in white markings and thus has no pigment. A grey colour arises due to a uniform mix of black and white hairs [14] [15]. The red phaeomelanin pigment type fades with age and has in many cases almost completely disappeared or diluted from phaeomelanic pattern areas. When diluted, it results in a white, dirty-white or creme colour [13].

2.3 Coat patterns in goats

Coat patterns are areas in the coat with different colours of hair. In 1990 Alan Turing suggested that morphogen (defined as signalling molecules that create responses in a cell, depending on its concentration [16]) causes morphogenesis, which can lead to (cell) patterns [17]. Morphogenesis can be described as follows "Morphogenesis is a biological process that causes a tissue or organ to develop its shape by controlling the spatial distribution of cells during embryonic development." [18]. So, depending on the amount of morphogen, cells can divide themselves into zones [19]. These zones can then have particular types of melanin.

The Agouti locus, earlier mentioned as the main factor that determines the colour of the coat, can result in many patterns [11], because of different combinations of dominant and recessive alleles (see Appendix A for a summary). Several of these alleles can result in a back stripe (also called dorsal stripe), a dark stripe over the back of the goat, related to the Bezoar, a wild ancestor of many domesticated goats. Completely black, brown or tan and white coats are also patterns of the Agouti locus, named as *no pattern*, *tan* and *white* respectively. Other loci are the Extension locus, the Albino Locus, the Brown locus and the Angora White Locus. These loci have an influence on the colour, but not specifically on the pattern of coats. Because the Extension locus affects the entire body of the goat, it can result in a complete eumelanic or phaeomelanic phenotype, depending on whether it has the dominant or recessive allele. The Albino Locus prevents melanin to be produced, resulting in a lack of pigment and thus colour in the coat. The Brown locus can make brown eumelanin replace black eumelanin in a light and a darker brown variation. The Angora White Locus results in a completely white coat. Furthermore, there are spotting patterns, of which Belt, Roan, Flowery, Goulet, Algarve, Barbari and Ticking result in white spots, and Moonspots result in light brown ovals. The noticeability of these types of spots can vary widely within each kind and can sometimes barely be noticed [11]. Just like come allele combinations can produce colours that look very similar to other sets of alleles. For example, Pheomelanin (usually resulting in a red, tan or cream colour) can also turn out to be pale to such an extent that it is almost white [20] [11]. This can make it difficult to determine the pigment type responsible for the colour of the coat.

3. Data

In this section, the data set used during the research will be covered. First, the data set will be described based on its characteristics and then the preparation of the data will be explained.

3.1 Description of the data

The data used for this research is delivered by the LFNL. This exists of eleven folders with a total of 1.945 unorganised files with a total size of 1,08 gigabytes. These files contained images, PDF files, Excel files and more, summarised in table 3.1 (Graphic Files consist of multiple file types; BMP, EPS, GIF, JPEG, JPG, PNG, THN and TIF files. These files varied from two kilobytes to 13,9 megabytes per file). Mostly data is about goats, but also some personal and sensitive data like images of people and online auctions could be found among the files. Images of goats consisted of both monochrome images and images in colour and could be either artistic representations of goats, as well as realistic representations. The exact age of these figures is not documented, except for instances where it has been written somewhere in the image itself.

File type	Amount
Corrupted files	12
Excel	1
Graphic Files	1.718
HTML & txt	2
Pdf	14
PowerPoint	2
Word	2
Duplicate files	194
Total	1.945

Table 3.1: Data types in the data set

'Duplicate files' are files with the same file names. Files with the same content but a different name are not included in 'Duplicate files'.

3.2 Preparation of the data

Before the data could be used for analysis and modelling, the data needed to be filtered on usability. This was a joint process, together with fellow student Michel Doré, in which the goal was to make one set of data, usable for both studies. The filtering process consisted of two cycles.

In the first filtering cycle, a division has been made, based on if an image can be considered usable or not regarding six requirements related to the image or the goat that is displayed.

1. The goat in the image must be of sufficient size.
2. The goat in the figure has to be in a straight, standing position (not grazing or seated).
3. The figure has to show the side view of the goat.
4. The figure has to contain a realistic representation of a goat.
5. The figure has to be a painting or drawing of a goat (no statue or other form of art).
6. The figure has to be in colour.

Through these specifications is ensured that all images show information that is needed and are in similar conditions. Monochrome images have only been removed for this study and not for the study of Michel Doré, since colour is not of importance for the head shape. Attempts to bring back colour from monochrome images to increase the size of the data set have not been satisfactory. Trials with coloured paintings that are made monochrome, and then are coloured again, generally showed a low colour intensity and mismatches in colour (see Appendix B).

After this first division, the second cycle of selection is performed. In this cycle, an image is classified as usable or not usable depending on whether or not the goat in the picture is:

1. A Dutch Landrace goat
2. A realistic representation of a goat.

3. A buck (a male goat)
4. Fully grown (in contrast with a kid, baby goat)

The classification in the second cycle is made together with the chairman of the board and a regional representative of the LFNL. Their expertise is used to distinguish between the different cases. Their opinion about a goat in a figure being realistic or not reduces the chance of unrealistic goats in the data set. Distinction is made between bucks, does and kids, because of their different body proportions, which are relevant when studying head shape.

The first cycle of filtering resulted in 136 images that met all of the requirements. This is a great reduction of data, that had mainly to do with many figures being monochrome or black and white, unrealistic or a photograph from after the year 1900 (in a few cases members of the LFNL could assure that a photograph was taken before 1900. These have been included). After the second filtering cycle, 60 figures are left, mainly due to figures containing a doe instead of a buck, and some figures not being realistic. In these 60 figures, 86 bucks are displayed. These are used to perform the analysis.

4. Methodology

This chapter describes the workflow designed to answer the research questions " *What colour(s) does the coat of the Dutch Landrace goat consist of?*" and "*What pattern(s) does the coat of the Dutch Landrace goat consist of?*". The individual steps will be explained and theoretically substantiated. All (input) data and code used in the methodology are available at https://github.com/MilanvanBeek/ThesisGCC, as well as (MATLAB) models.

Automated image processing generally consists of four components; preprocessing, detection of matters of interest, feature extraction and finally classification [21] [22]. The first step, preprocessing of the data, has partially been done in the previous chapter, chapter 3.2 *Preparation of the data*, by cleaning the data, and will also be briefly mentioned in this chapter. Detection of matters of interest and feature extraction will be the main subject of this chapter. In this particular study, the classification step is irrelevant, because the objective of the study is to obtain information about the colours and patterns of the Dutch Landrace goat specifically, and not to classify those in for example other existing goat coat patterns. To answer the research questions, the following data pipeline has been designed:

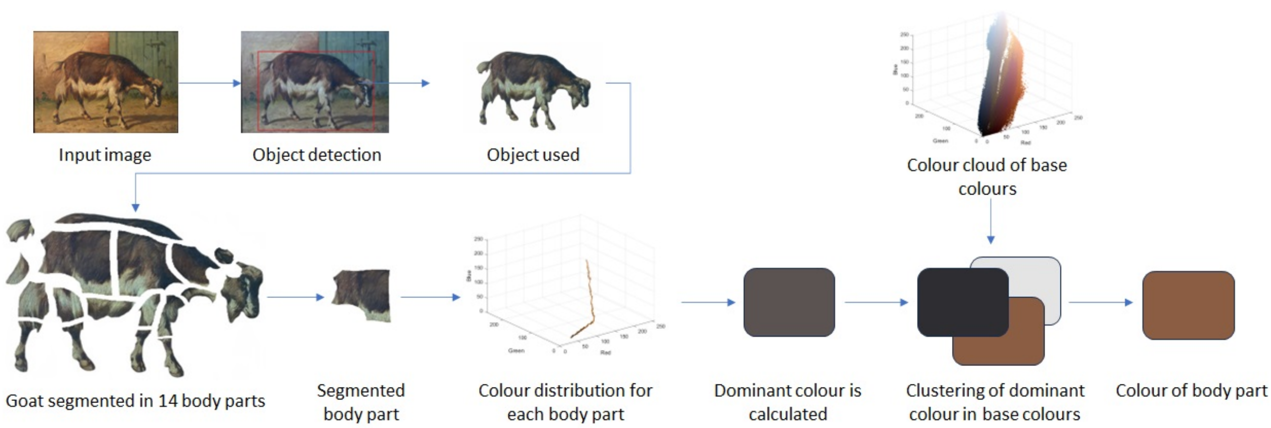

Figure 4.1: Data pipeline visualising the steps in the methodology

4.1 Colour normalisation

Before the data pipeline is discussed, colour normalisation is performed. This is done to take the variation of illumination in an image into account, but also potential gamma corrections and reduction of colour intensity, as described in chapter 2.1. To do this, the *illumgray* function in MATLAB is applied [23]. With this function, the grey world algorithm is used to estimate the illuminant of an image. This algorithm assumes the average of an image is grey. Because of this, it is important to use an image with a wide colour distribution. This is why this step is done before removing the background of the image. By assuming the average of an image is grey, the colour channels are normalised [24].

4.2 Detection and segmentation of goats

Now colour normalisation is performed, it is necessary to first isolate the objects of interest, before we can look at colours and patterns. Doing this will assure that when colours are fed into a model, only relevant colours are used. This is done by segmenting the goat out of the painting. For this purpose, a new segmentation model has been used which was released earlier this year, named Segment Anything Model [25]. Segment Anything is a model pre-trained on the SA-1B data set, existing of eleven million images, resulting in over one billion masks. In a comparison with RITM [26] (one of the segmenters that was chosen as a benchmark), Segment Anything outperforms RITM on 17 out of 23 data sets. Besides, it has a very good zero-shot performance, which makes it one of the best segmentation tools available for non-specific purposes [25]. Points, (bounding)boxes and text can be used as input for the prompt encoder, to generate masks for the input image.

Here YOLOv8 is used for providing the input images with bounding boxes [27]. Yolov8 is currently the newest model in the YOLO series. The pre-trained YOLOv8 model yolov8m has a mAP50-95 of 50,2% when benchmarked against the COCO data set, containing 200.000 images with object detection annotations. The weights of this model have been fine-tuned by fitting self-labelled training data (using www.makesense.ai). By doing this, the mAP50 rose to 74,1%, with a smoothed mAP50 of around 61% and an F_1-score of 0,747.

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.1}$$

The smoothed F_1-score would be approximately 0,61 (details about the performance are available in Appendix C). This segmentation process is done in collaboration with Michel Doré.

4.3 The coat colours of Dutch Landrace goats

As mentioned in chapter 1.2.1, the exact colour of a single pixel is not reliably detectable, and (if not more important) not significant, since the general colour that is tried to visualise is of value, and not the colour of a particular pixel. Because of this, the colour of a goat has to be determined by its pixel cloud, all pixels relevant to the object. The pixels in this pixel cloud can then be represented by one (or multiple) dominant colour(s), by clustering the colours and calculating the cluster mean.

For a clustering or classification problem, the Euclidean distance is often used (for example K-means and K-nearest neighbour) [28] [29]. But this assumes spherical distributions of clusters, where the distance between the centre of the cluster to the edge is determined by the radius of the sphere. Because the pixel cloud is most probably not spherical (because of correlation between the different dimensions), and the distribution of colours does not tend to be constant, a Gaussian mixture model is used to cluster coat colours. Here the shape of the Gaussian mixture model is determined by the covariance matrix, which makes it possible for the shape to be an ellipsoid. This method also appears to be suitable in other studies where colours have been clustered and a dominant colour is computed [30] [31]. The advantage of ellipsoid shapes, compared to a spherical shape, is that an ellipsoid most likely will fit better on variables that are correlated to each other. The multivariate Gaussian distribution is given by the following equation [32],

$$\mathcal{N}(x_i|\mu_k, \Sigma_k) = \frac{1}{(2\pi)^{(p/2)}|\Sigma_k|^{1/2}} \exp\left\{-\frac{1}{2}(x_i - \mu_k)^T \Sigma_k^{-1} (x_i - \mu_k)\right\}. \quad (4.2)$$

When the dominant colour of an input image is computed (see Appendix D for the colour cloud of the input image and the mean and standard deviation), it can be grouped into a base colour, that finally determines the colour of a coat. As mentioned in chapter 2.3, (a mixture of) three pigment types decide the colour of the coat of a goat. This can result in situations where determining the exact colour of a coat can be challenging. The colour grey is a blend of white and black hairs, and beige and cream are a dilution of phaeomelanic areas. Because of this, the difference between a colour being brown, cream, red or tan, and grey or white, is arbitrary. Therefore, the base colours that dominant colours will be clustered in are *black*, *brown* and *white* (see Appendix E for the base colours, the colour clouds and its mean and stand deviation), grouping other shades of colour as tan, red and cream under the colour brown. Biologically these colours do have different origins since they are caused by different pigment types, but because the goal of this research is to identify the colour patterns, and not the underlying genetics causing those patterns, this is immaterial.

The base colours are retrieved out of Gaussian mixtures as well. In this study, these mixtures are composed by inserting ten images of goat coats of each colour, similar to other studies [30] [33]. These goat coats are selected based on species known for their colour (for black for example the Black Bengal Goat and the Anatolian Black Goat, for brown the Nigerian Dwarf Goat and the Alpine goat and for white the Saanen and Jonica Goat). Then the function *cluster* is used to cluster the dominant colour of the colour cloud to one of these three clusters of base colours. This cluster function gives the component with the highest posterior probability for a new point (in our case a new dominant colour)[34] which can be calculated with the Bayes theorem, based on multiplying the prior probability distribution with the likelihood. Because the output colours are grouped into base colours, little colour details will not have a big influence on the result of the colour extraction.

4.4 The coat patterns of Dutch Landrace goats

Now that we know how to determine the colour of an image, we need to find patterns in the coat. Multiple studies regarding patterns on animals have used edge detection models [35] [36]. Edge detection models detect and locate edges in a figure by transitions of colour intensity [37]. Canny edge detection [38] was used, since multiple studies showed its high performance [39] [40] [41], and it focuses on three performance criteria; good detection, good localisation and only responding once to an edge [38]. However, attempts with the Canny edge detection method resulted in unsatisfactory outputs. When experimenting with upper and lower thresholds, important edges were not detected, even though other less obvious edges and noise did show up (see Appendix F). This happened despite the fact that Canny is relatively insensitive to noise [41]. Therefore, another method has been utilised.

With this second method, the pattern of a goat its coat is not defined by its edges, but by its emerging colours on specific regions of its body. By computing the colour for each relevant body region, coat patterns can be defined. To decide which body parts of a goat are needed to determine the colour for, an inventory is made based on Sponenberg's Genetics of Goat Color [11]. Here every part of a goat's body that is associated with a pattern type is listed, as well as every colour named. These body parts then can be segmented to determine their colour. In this study, because of the relatively small amount of data, the colour of each body part has been assessed manually. In total, 20 (partially overlapping) body parts have been mentioned. Of these body parts, five could not or scarcely be observed from the side view that the goats in the selected painting are in. The other 15[1] are included in the study. The visible and non-visible body parts are listed in Appendix G,

[1] Head, Ear(s), Chin & throat, Neck, Anterior half, Posterior half, Belly, Dorsal region, Front limbs, Rear limbs Upper legs, Lower legs, Front of front legs, Back of thighs and tail

as well as a visualisation of the observed body parts in Appendix H.

When the colour is decided for each of these body parts for the input images, we then have an overview of the different colour patterns that occur in the Dutch Landrace goat.

Finally, the distance between goats can be calculated. This can be done by using the Mahalanobis distance. In contrast with another common distance metric, the Euclidean distance, where features or dimensions are treated equally and independently, the Mahalanobis distance uses the covariance matrix (just like the Gaussian mixtures) to weigh the distance to the variation of each component (which scales the data) and take into account the correlation between different dimensions. This way, the Euclidean distance between two points and the mean can be equal, while the Mahalanobis distance shows differences in distance. The Mahalanobis distance is given by

$$D = \sqrt{(x-m)^T C^{-1} (x-m)}, \tag{4.3}$$

where x is an observation, C^{-1} is the inverse covariance matrix and m is the mean of each attribute. When the distance between goats is small, their coat characteristics are similar and vice versa. These distances can be plotted by using multidimensional scaling (MDS), a lower-dimensional representation of the data. This way, goats with different and rare patterns are placed further away from the centre and similar patterns are closer to the centre.

5. Results

In this chapter, the results of the research are presented. With these results, the research questions will be answered. The raw data used in this chapter can be found at https://github.com/MilanvanBeek/ThesisGCC. The results regarding the head shape of the Dutch Landrace goat can be found in *Do 2D representations using Procrustes analysis accurately represent the head shape of the Dutch Landrace goat in comparison to the consensus shape?*, by Michel Doré.

5.1 Colours

Of the 86 goats that have been assessed, 11 goats contained body parts that were not visible due to other animals or objects blocking them. When looking at colours occurring in the coat of the other 75 Dutch Landrace goats in paintings, we can see some noteworthy differences. One-third of goats (33,3%) contained the colour black. With the colour brown being observed in 34,4% of goats, it is only slightly more common than black. The colour white on the other hand, can be seen substantially more frequently in these goats. 63,4% of goats contained the colour somewhere on their coat.

This also becomes clear when we look at combinations of colours. As shown in table 5.1, predominantly white coats are most common, with combinations of white with black and white with brown as second and third respectively. Noticeable is that a solely black coat pattern is relatively rare, as well as coats containing all three colours. Since the colours black and brown both can be seen almost as often, but the individual appearance of brown is relatively much more common, we can conclude that black occurs more often in combination with other colours than brown.

Colour (combinations)	Occurrence (in %)
Black	1,3%
Brown	9,3%
White	32,0%
Black & Brown	10,7%
Black & White	24,0%
Brown & White	17,3%
Black, Brown & White	5,3%

Table 5.1: Colour combinations of the Dutch Landrace goat

5.2 Patterns

The distribution of colours per body part of the Dutch Landrace goat is shown in table 5.2. The body part 'front of front legs' is omitted from the data, because of the similarity it shows with the rest of the legs. Only in one case, the colour of the front of front legs did not occur in another body part related to the front limbs. This leaves us with 14 body parts, for which there are three colour options. This gives 3^{14} = 4.782.969 different colour combinations possible in the goats. The 75 different goats resulted in a total of 42 different observed patterns. The distribution of patterns is skewed and because of this high number of pattern possibilities and a much smaller amount of data samples, it must be noted that it can be misleading.

	Head	Ear(s)	Chin & throat	Neck	Anterior half	Posterior half	Belly	Dorsal region	Front limbs	Rear limbs	Upper legs	Lower legs	Back of thighs	Tail
Black	17,3%	21,3%	16,0%	18,7%	6,7%	10,7%	13,3%	22,7%	9,3%	8,0%	10,7%	16,0%	10,7%	16,0%
Brown	36,0%	37,3%	33,3%	40,0%	34,7%	30,7%	24,0%	16,0%	33,3%	30,7%	34,7%	26,7%	32,0%	26,7%
White	46,7%	41,3%	50,7%	41,3%	58,7%	58,7%	62,7%	61,3%	57,3%	61,3%	54,7%	57,3%	57,3%	57,3%

Table 5.2: Distribution of colour per body part

The division of colours shows an expected pattern, based on the fact that the colour white is seen most, and black the least. On average 14,1% of observed body parts is black 31,1% brown and 54,8% white. When we compare this to 33,3% of goats containing the colour black, and 34,4% brown, we can conclude that when brown is found in a goat, it on average is likely to find twice as much brown than black will be found in a goat containing black in its coat.

White is most common in every body part, however, in both the ears and neck, the distribution of the colour brown and white are almost equal to each other. The dorsal region is the only body part where black is not the least common colour. White is still the most common, but black occurs 1,42 times as much as brown.

Within the 42 different patterns, some groups can be formed based on their recurring pattern (see Appendix I for all observed patterns). This will then lead to four pattern types that are more heavily represented. These are shown in table 5.3. The completely white and brown patterns show in all observed body parts the same white or brown colour. Though the goat does not necessarily need to be solely white or brown. It could be that other colours are present in the coat as well, but not to such an extent that it affected the dominant colour of a body part. So the *dominant* colour of their body parts is overall white or brown. Besides the fully white and brown patterns, another emerging pattern is that of the dorsal stripe (earlier mentioned in chapter 2.3). When the dorsal region is dark (either black or brown), and another colour than the anterior half, posterior half and the back of thighs, it can be concluded the goat has a dorsal stripe. The fourth type, the 'Black head with white body', has got a black head, black ears and a black chin, throat and neck, but is white on the rest of its body. Together, these four groups represent approximately 60% of all observed goats.

Pattern	Occurrence (in %)
Completely white	32,0%
Dorsal stripe	13,3%
Completely brown	9,3%
Black head with white body	4,0%

Table 5.3: Four main colour patterns and their proportion

When we focus on the group of goats with a dorsal stripe, it can be noticed that all observed dorsal stripes are black and in 50,0% of the goats, a black belly is found. In 30,0% the black stripe continues all the way down the tail. Furthermore, a big proportion of the goats with a dorsal stripe is brown. Besides the belly and tail 50,0% is completely brown. The other goats can have some black body parts, like on the lower legs and head. Only one out of the 10 goats with a dorsal stripe has a predominantly white coat.

If we zoom in on the pattern group of goats with black heads (including ears, neck and chin and throat), we find that about 9,1% has got a fully black body as well, 27,27% has a fully white body, but the majority have got a mixture of black and white on the coat of the body. Brown was found only on the rear limbs of one goat, so this colour is relatively rare in combination with a fully black head.

Finally, if we take a closer look at the legs, we can see that 78,7% of goats have a uniform leg colour, of which nearly 50% is white, 21,3% is brown and 6,7% is black. The division of front and rear legs and of upper and

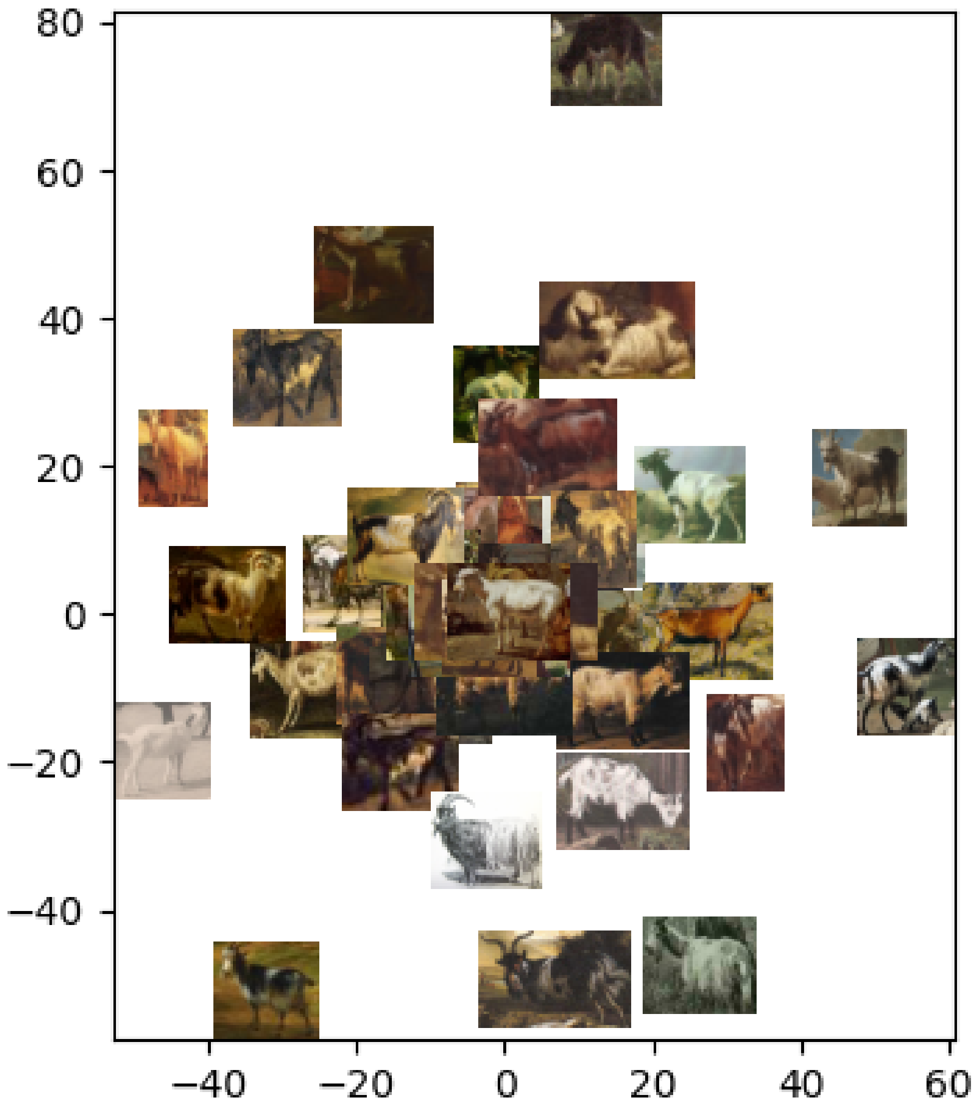

Figure 5.1: Distances between goats visualised in a 2D plot

lower legs have respectively in 88,0% and 86,7% of goats a uniform colour. When we differentiate between the front and the rear legs, one-third of the legs is a combination of black and white, where 66,6% has black front legs, and two-thirds is brown and white, where 66,6% has brown front legs. For the upper and lower legs, 40% is black and brown, where all upper legs are brown and all lower legs black, 20% is black and white, where 50% has black upper legs and 50,0% white upper legs, and 40% is brown and white, where 75% has brown upper legs, and 25% has white upper legs.

When we visualise the distances between goats, calculated with the Mahalanobis distance and visualised by multi-dimensional scaling, we get a two-dimensional image (see figure 5.1 on page 23). When reducing from 14 to two dimensions, information is lost, so the figure can be used only as a visualisation. In this visualisation, 'outliers', in this case, goats with uncommonly observed coat patterns, are located on the outside, while more similar patterns are located near the middle. This also corresponds to the results mentioned earlier; on the outside, more random-looking patterns are plotted, while the more we go to the centre, the more patterns can be observed that are closer to each other. These random-looking patterns include for example goats with a uniform colour, except for the thighs or necks (something that is not related to common patterns). In Appendix J this plot is visualized, where is been zoomed in on the centre of the plot.

6. Conclusion

This study aimed to identify the colours and patterns in the coat of the Dutch Landrace goat, to give members of the LFNL clarity and consensus about the coat colour phenotype. This is done to get a better understanding of what the Dutch Landrace goat historically looked like and to establish breeding goals. For this purpose, the following research questions have been formulated "*What colour(s) does the coat of the Dutch Landrace goat consist of and how is this distributed?*" and "*What pattern(s) does the coat of the Dutch Landrace goat consist of and how is this distributed?*

Regarding the colour, it has been found that the colours black, brown and white occur in respectively 33,3%, 34,4% and 63,4% of goats. The three most occurring colour combinations are 'white', 'brown and white' and 'black and white' respectively. Both these statistics show that white is the colour in this goat species that is most common.

Four reoccurring patterns have been observed, that together occur in 58,3% of all observed goats. In order of frequency, these patterns are 'completely white', 'dorsal stripe', 'completely brown' and 'black head with white body'. The first three of these patterns are also mentioned in the literature review, as patterns caused by the Agouti locus. Also is mentioned that the dorsal stripe (related to the Bezoar) is a dark (black or brown) stripe on the back of a goat. The dorsal stripe pattern in all observed cases from the data contained a black stripe. No brown dorsal stripes have been observed.

7. Discussion

First and foremost, it must be mentioned that a limited amount of data could be used during this study. The limited amount of data and the image selection procedure makes selection bias more likely. Especially since goats have been selected based on their appearance by members of the LFNL, their image of this goat determined what samples ended up in the data set. This makes that the results may not be entirely repressive, but it gives a good indication of the distribution of colours and patterns in the Dutch Landrace goat. Also, with this limited amount of data, a suitable database has been established. This database can in the future be used for other research related to the Dutch Landrace goat, but also for other painting or goat-related studies and it is useful for educational purposes of the LFNL.

In the data set delivered by the LFNL, some personal and sensitive data like images and information of people and online auctions could be found. This has been mentioned to the providers of the data and because of privacy reasons, these files have directly been removed from the data set.

Because certain body parts are used to decide the colours and patterns of a coat, small details in the coat may be lost. This can happen when these details are so small that they do not influence the dominant colour of that particular body part. This is a limitation of this research. However, by choosing this method, the new segmentation technique of Segment Anything is applied. Even though Segment Anything is relatively new, in 2023 alone it has been studied a lot in the medical field. In multiple studies, results have not been satisfactory [42] [43]. In this study, however, Segment Anything has been applied to paintings of animals, where the results have been sufficient. It must be noted that the implications in this study have been very different, but it goes to show that Segment Anything on more general images and larger objects like animals is feasible, even in paintings. Especially the latter can be relevant for studies analysing paintings, or similar forms of art. However, in future studies, it is still interesting to study the importance of these small details for the pattern of the coat, since this could give more insights to goat coat patterns. Also, when the method proposed in this paper is applied to other species, where historical goat coats are documented, the effectiveness of the method can be tested and it can be studied if there is a similarity in the way these coats developed over time. This information could in turn confirm or complement the findings in this research or disprove it.

Also, comparing the genetics of the Dutch Landrace goat regarding its coat, to the findings of this paper might discover valuable information. This way the questions answered in this study will be researched with different methods from multiple fields.

Another remark is the fact that to determine existing patterns on the Dutch Landrace goat, estimates have been made regarding coat colour. However, in some cases it is hard to determine the exact colour of a coat, by hand as well as by the proposed method. This is especially the case when looking at paintings of goats, instead of actual goats. To overcome this challenge as best as possible, multiple steps have been applied, as described in the methodology. Still, the base colour white, determined by the Gaussian mixture model, is not completely white. White is located at the absolute end of the colour spectrum of which colours are grey or black with an RGB range of over 95%. So if while clustering some colours are grouped that are not at the far end of the spectrum, the average quickly changes from pure white to a whitish or grey colour. However, the outcome of the study is not affected by this phenomenon, because the colours are divided into the base colours manually.

Also, as said before, paintings and other forms of art have been used for this research. It is possible, that the artist of these artworks made (little) deviations from reality regarding the appearance of a goat. This could influence the outcome and conclusion of this research. To minimize this chance, a selection process has been set up, where a selection was made based on (among others) if the works of art are deemed to be realistic representations of the Dutch landrace goat. This selection process has been performed by members of the board of the LFNL. It could still be the case, however, that some artistic deviations made it through the selection, because it is impossible to rule it out completely, since these artworks are the only reference point of historical coats of the Dutch Landrace goat. Scarcity (and thus high costs) of paint, are not expected to have a big influence on the colours used in paintings. As mentioned in Chapter 2.1, since 1800 scarcity of paint colours was resolved by improved international trade.

Finally, this paper has focused on the colour phenotype of the coat of the Dutch Landrace goat from paintings from a sideways perspective. For that reason, some body parts related to coat patterns could not be studied. For further research, it would be relevant to analyse other perspectives. Especially a front perspective could be valuable, since there are some detailed facial patterns related to specific goats [13]. This can lead to new insights and more detail regarding the specifics of the coat. In addition to the colour of the coat, the length of the coat is also of importance. More specifically distribution of the coat length of Dutch Landrace goats in paintings from before 1900 has not been covered in previous studies.

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Appendices

A. Agouti locus patterns

Pattern group	Allele
White	
	White
	Tan
	Shaded red
	Black mask
	Sable
Tan with black trim	
	Bezoar
	Wild riedell
	wild kolozie
	Badgerface
	Serpentina
	Caramel
	Tan sides
Black and tan anterior or posterior divisions	
	Peacock
	San clemente
	Repartida
Grey or nearly grey	
	Grey
	Pygmy agouti grey
	grey striped
Black with tan trim	
	Toggenburg
	Black and tan
	Eyebar
	Angel
	Lateral stripe
Nearly black	
	Mahogany
	Tan cheek
(nearly) Completely black goat	
	No pattern

Table A.1: Overview of the different alleles by pattern group [11]

B. Restoring colour from monochrome images

Figure B.1: Top: Original image, middle: image in B&W, bottom: restored colours

C. Performance results YOLOv8

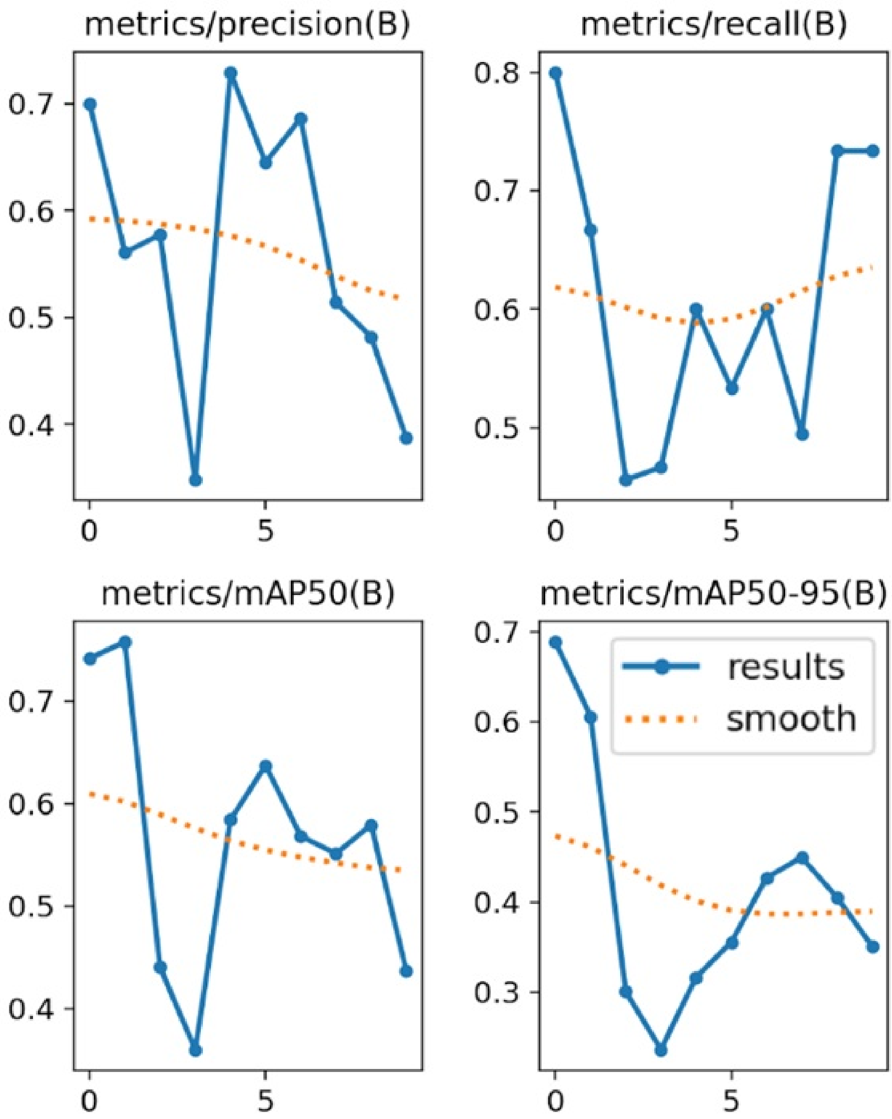

Figure C.1: Performance results of the first ten epochs of the custom trained YOLOv8 model

D. Input image

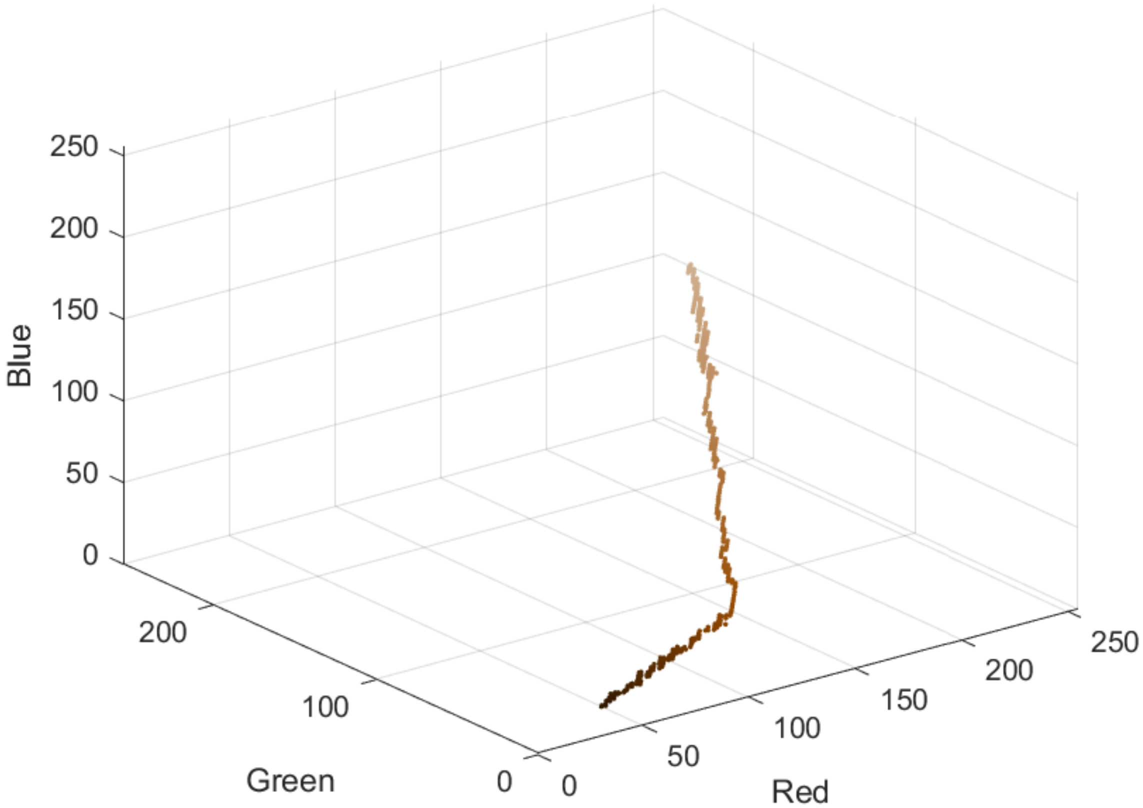

Figure D.1: Visualisation of the RGB values of an input image

Property	Value		
NumVariables	3		
DistributionName	gaussian mixture distribution		
NumComponents	1		
ComponentProportion	1		
SharedCovariance	0		
NumIterations	3		
RegularizationValue	0		
NegativeLogLikelihood	685307,6362		
CovarianceType	full		
mu	136,47	85,18	33,59
Sigma	2,1646e+03	1,9591e+03	1,7516e+03
	1,9591e+03	1,9436e+03	1,9192e+03
	1,7516e+03	1,9192e+03	2,0751e+03
AIC	1,37e+06		
BIC	1,37e+06		
Converged	1		
ProbabilityTolerance	1,00E-08		

Table D.1: Properties of a Gaussian mixture distribution of an input image

E. Base colours

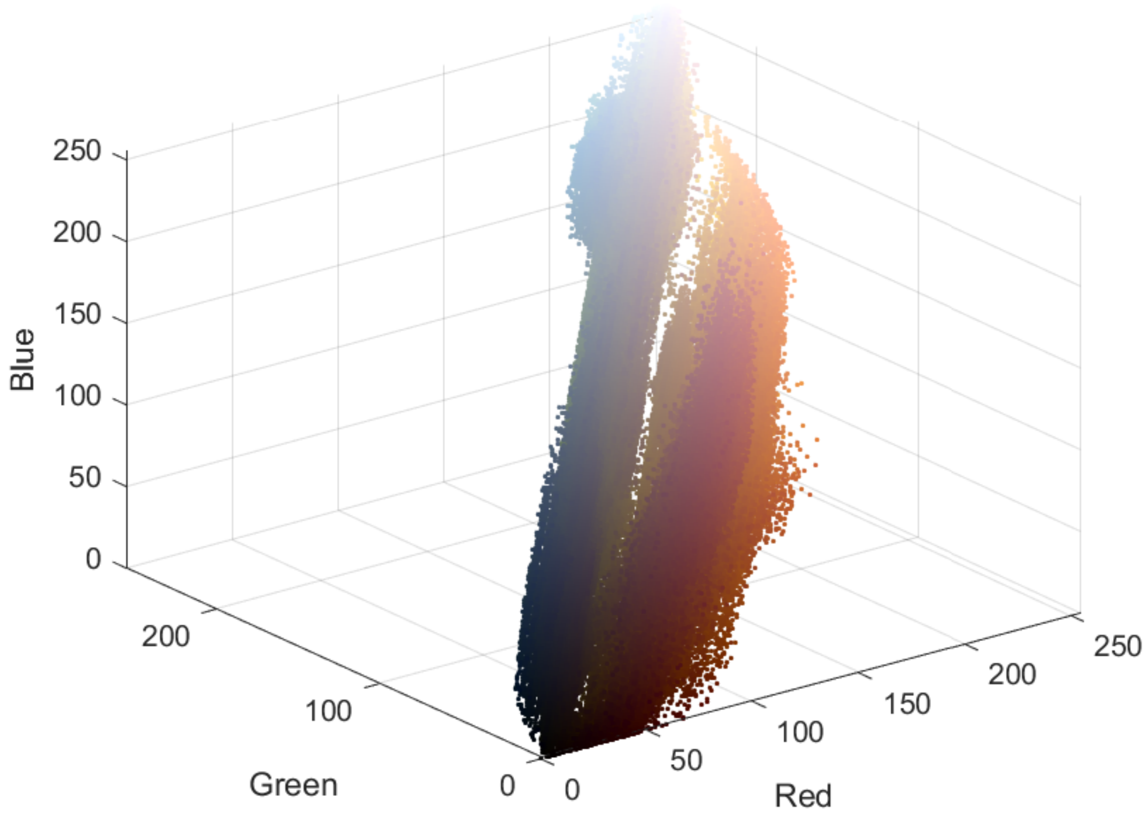

Figure E.1: Visualisation of the RGB values of the base colours

Figure E.2: Visualisation of the base colours

Property	Value		
NumVariables	3		
DistributionName	gaussian mixture distribution		
NumComponents	0,4046	0,3070	0,2884
ComponentProportion	1		
SharedCovariance	0		
NumIterations	21		
RegularizationValue	0		
NegativeLogLikelihood	2,7891e+07		
CovarianceType	full		
mu 1	175,92	177,78	172,34
mu 2	139,28	92,54	66,07
mu 3	46,09	46,09	49,01
Sigma 1	1982,4	1879,6	2035,7
	1879,6	1817,5	1973,7
	2035,7	1973,7	2213,3
Sigma 2	1850,8	1703,6	1282,6
	1703,6	1708,5	1319,9
	1282,6	1319,9	1213,7
Sigma 3	672,0	701,5	759,5
	701,5	747,0	816,3
	759,5	816,3	908,9
AIC	5,5782e+07		
BIC	5,5782e+07		
Converged	1		
ProbabilityTolerance	1,00E-08		

Table E.1: Properties of a Gaussian mixture distribution of the base colours

F. Results Canny edge detection

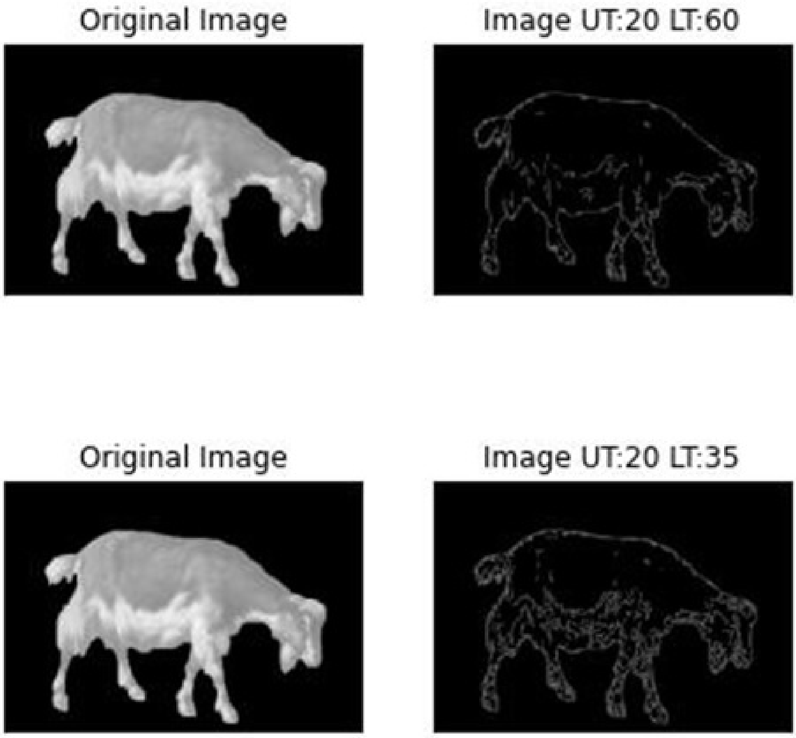

Figure F.1: Results of Canny edge detection with an upper and lowe threshold or respectively 20 & 60 and 20 & 35

G. Visible and non-visible body parts

Visible body parts	
	Head Ear(s) Chin & throat Neck Anterior half Posterior half Belly Dorsal stripe Front limbs Rear limbs Upper legs Lower legs Front of front legs Back of thighs Tail
Non-visible body parts	
	Inside of legs Muzzle Facial stripes Pernium Scrotum/Udder

Table G.1: Mentioned body parts when describing coat patterns [11]

H. Observed body parts

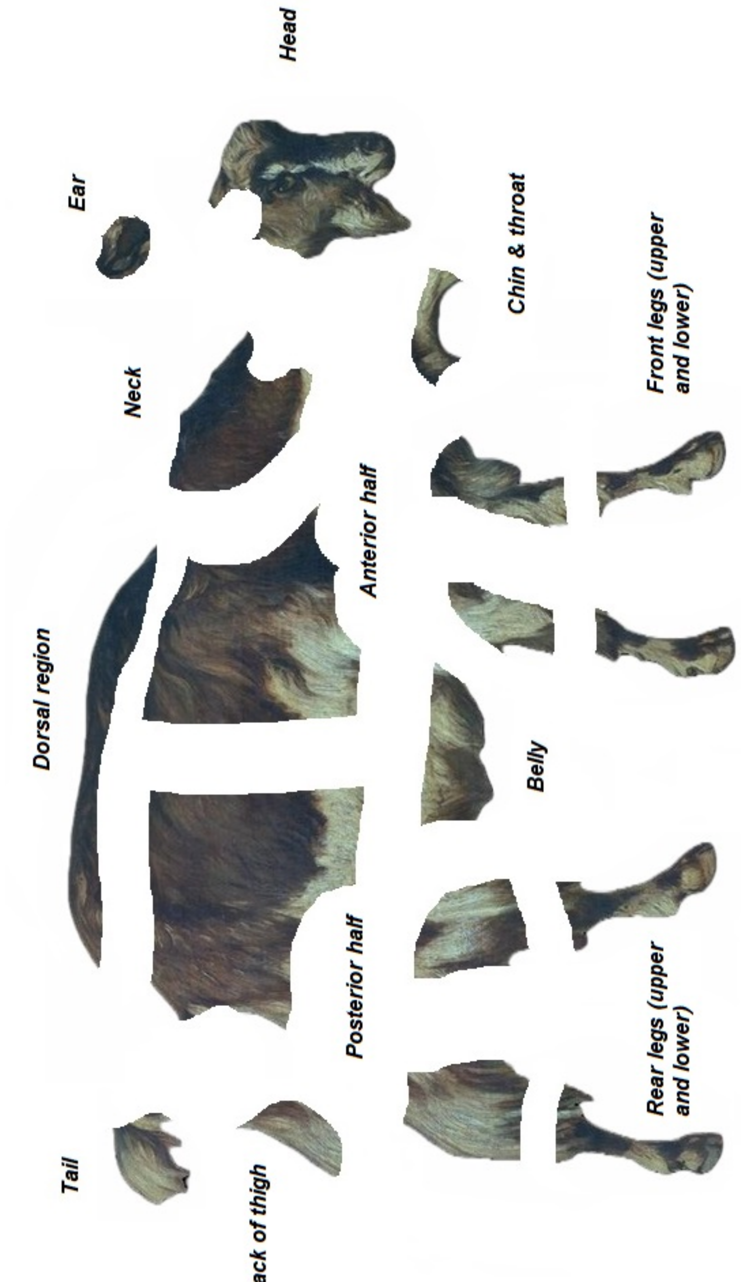

Figure H.1: Body parts of the goat, for which the dominant colour is determined (with legs being divided in front, rear, upper and lower)

I. Encountered patterns

Pattern	Occurrence (in %)
33333333333333	31,2%
23223222222222	1,3%
31333333333313	1,3%
33323232333323	1,3%
11113333333333	3,9%
33333113333311	1,3%
22222333333323	1,3%
22222222222222	10,4%
11113111111133	1,3%
22222211222221	2,6%
33332323232333	1,3%
22222211222222	2,6%
22222323232233	1,3%
22222221222221	1,3%
22222332232232	1,3%
22222221222122	2,6%
33333133313311	1,3%
32322232222222	1,3%
33333333333133	1,3%
11111111111111	1,3%
22222223222322	1,3%
31311131333331	1,3%
11113313333333	1,3%
11111131321311	1,3%
22323331333333	1,3%
22222233222223	1,3%
22223333333333	1,3%
11111131111111	1,3%
22222211232121	1,3%
22323223222132	1,3%
11313113111131	1,3%
31133333333333	1,3%
22222221222222	1,3%
11113333131133	1,3%
12222211222222	1,3%
11113331111111	1,3%
22322323322222	1,3%
11111333131133	1,3%
22222333222322	1,3%
31333331333311	1,3%
33313333333333	1,3%
22222222333233	1,3%

Table I.1: All observed patterns and their frequency, where 1 = black, 2 = brown and 3 = white. The body parts from left to right are Head, Ears, Chin & Throat, Neck, Anterior half, Posterior half, Belly, Dorsal region, Front limbs, Rear limbs, Upper legs, Lower legs, Back of thighs and Tail

J. Zoom of MDS visualisation

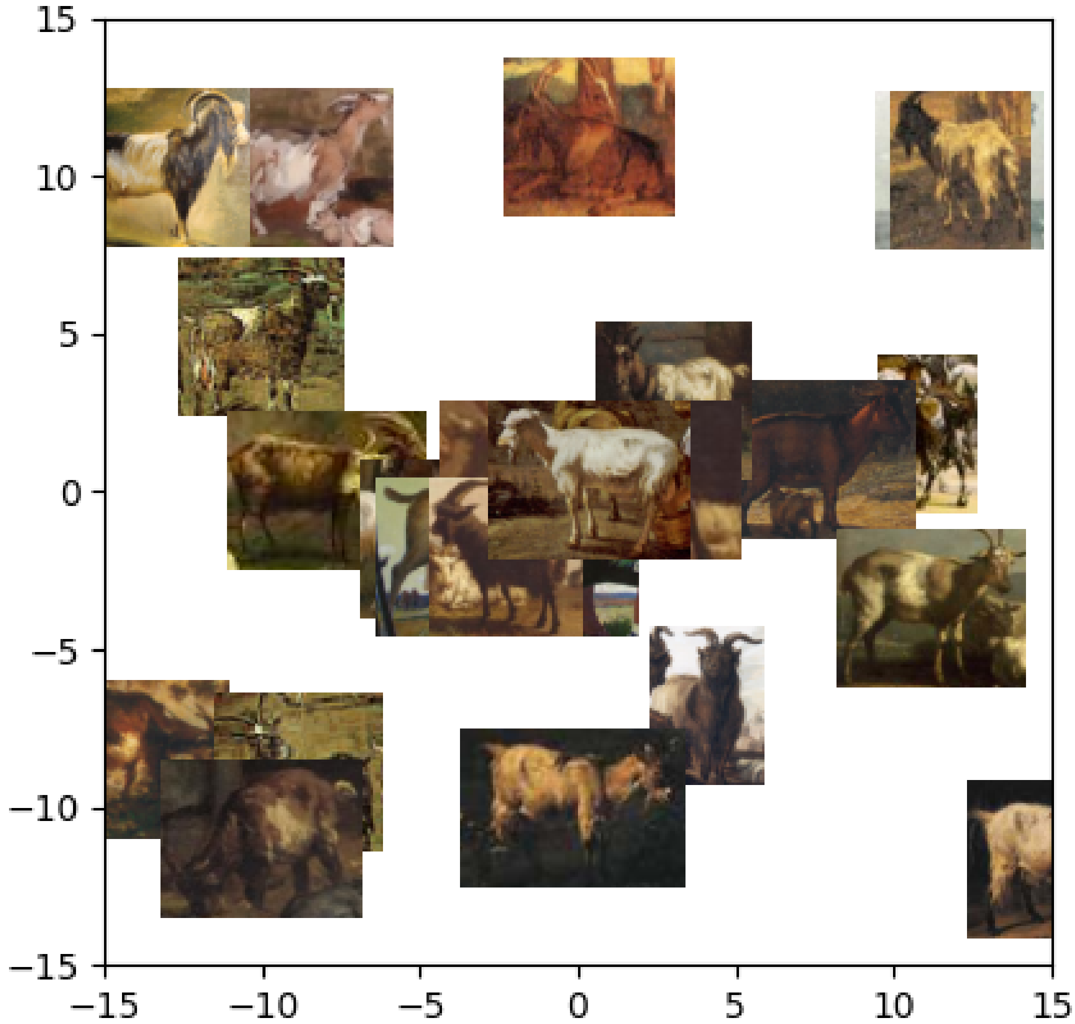

Figure J.1: Distances of between goats visualised in a 2D plot, zoomed in on the centre