Automated Detection of Anemia in Small Ruminants Using Non-Invasive Visual Analysis based on BIC descriptor

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***Abstract*—This study presents an automated method for the detection of anemia in small ruminants using non-invasive visual analysis of the ocular conjunctiva. The method involves image processing techniques and machine learning algorithms to extract relevant features and classify animals into different infection levels. The dataset consisted of photographs taken from real animals, with each animal evaluated based on the FAMACHA scale and hemoglobin level measurements. A total of 114 images were analyzed, including both sheep and goats, representing various stages of infection and distinct fur types. BIC (Border/Interior Classification) descriptor was used to extract information from the conjunctiva and two different classifiers were tested: SVM and KNN. The experimental results showed promising outcomes.**

I. Introduction

In recent years, the goat and sheep herds in Brazil have been growing exponentially. The northeastern region of the country holds approximately 57.5% of the sheep population and 91.6% of the goat population of the total herd, according to data from the Brazilian Institute of Geography and Statistics (IBGE). This demonstrates the importance of this activity for the region's economy and the need for research to improve production [1].

One of the main challenges faced by small and medium-sized producers is keeping animals free from gastrointestinal parasites, which has hindered the sector's growth and poses a serious health problem. Therefore, there is a need for more effective and accessible methods of diagnosing infections and treatment [2].

The FAMACHA (Fafa Malan Chart) method stands out in combating parasite infections in small ruminants. However, its application depends on variables that only experienced professionals can take into account. The method consists of a scale color chart that demonstrates the levels of conjunctiva coloration in a healthy animal compared to an animal with a high degree of parasite infection. To apply the method, a trained professional must expose the conjunctiva (inner part of the eyelid) and compare it to the scale, thereby assigning one of the five FAMACHA levels to the analyzed animal. A model of the scale used by the FAMACHA method can be observed in Fig. 1.

Levels A(1) and B(2) correspond to a considered healthy animal, while level C(3) corresponds to an animal with an undefined status, which is at the discretion of the professional to classify. Levels D(4) and E(5) correspond to an infected animal, with level E(5) indicating a severe infection.

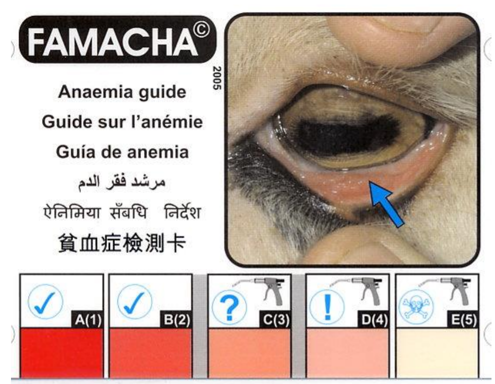

Fig. 1. The FAMACHA chart model.

Applying this method requires professionals to have experience and knowledge in animal handling, as well as consider factors such as daylight, animal age, gender, and lactation period in the case of females. The FAMACHA method also relies on the duration of conjunctiva exposure and produces varying results depending on the professional [3].

Fernandes et al. [3] discuss the identification capabilities of selective anemia diagnostic methods such as FAMACHA and PEG (Parasite Eggs per Gram of Feces). They also evaluate the effectiveness of these methods in preventing increased resistance to anthelmintics by accurately identifying truly infected individuals (true positives), thus avoiding the unnecessary treatment of uninfected individuals and ensuring appropriate treatment for infected ones. The authors emphasize

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the subjectivity of interpreting FAMACHA levels and the crucial need for training test evaluators.

Vieira [2] emphasizes the importance of research in the field of anemia diagnosis in ruminants, highlighting not only the commercial aspect but also the risks to human health posed by the ingestion of materials contaminated with chemical residues from indiscriminate anemia treatment.

Molento et al. [4] provide a more detailed evaluation considering the percentages of helminths and FAMACHA scale levels. They assessed twenty-two different animals and validated the diagnosis obtained by the FAMACHA method by comparing it with the diagnosis obtained through hematocrit examination.

Alencar et al. [5] present the sanitary profile in a specific region, in this case, the Sertão region of Pernambuco. The study documented various failures in animal health management, taking into account the structures of the farms. Another important factor identified was the incorrect deworming techniques employed, as well as the lack of access to efficient technical assistance to aid in management control.

This study aims to present a methodology for detecting anemia in small ruminants that can determine the degree of infection in an animal by using image processing techniques applied to conjunctiva photographs.

The remainder of the article is organized as follows. Section 2 presents related works, discussing previous research and studies in the field. In Section 3, the methodology for detecting anemia in small ruminants is described in detail. Section 4 presents the results obtained from the experiments conducted using the proposed methodology. The findings and analysis of these results are discussed. Finally, in Section 5, the conclusions of the study are provided, summarizing the main findings, highlighting the significance of the methodology, and suggesting potential areas for further research.

II. Related Works

Hermoza et al. [6] develop a screening tool that uses photographic images of the patient's ungueal bed to determine if they have a high, medium, or low possibility of having anemia. The images underwent processing to extract regions of interest from each fingernail. Datasets were generated, and a neural network was employed to predict the risk of anemia. Preliminary findings reveal that the proposed anemia semaphore achieves a sensitivity of 0.79 and a specificity of 0.91. These outcomes suggest that the anemia semaphore could serve as a screening method, reducing the need for blood tests and shortening the evaluation time from 15 minutes.

Mohammed et al. [7] focuses on the collection of data from 539 participants, extracting 10 related features. The aim was to develop an accurate anemia prediction system by applying three rule-based classification techniques: ZeroR, OneR, and PART. These techniques were used to extract relevant information from the anemia dataset and establish "If-Then" rules. Among the techniques applied, PART exhibited the highest accuracy of 85%, surpassing both ZeroR and OneR. The authors highlight that the results from these techniques serve as a benchmark for further exploration of other applied techniques and provide valuable insights into the underlying rules within the anemia dataset.

In the study of Tamir et al. [8], a mechanism was designed for the automated detection of anemia through a non-invasive visual method. The process involves analyzing the anterior conjunctival pallor of the eye to detect anemia. It quantifies the conjunctival color by analyzing digital photographs taken with a smartphone camera of appropriate resolution under suitable lighting conditions. These images were processed to obtain the red and green component spectra of the conjunctiva color and compared against a threshold to determine whether the patient is anemic or not. The authors conducted an experiment with 19 patients, and the developed methodology was a satisfactory result in 15 cases.

Fuadah et al. [9] developed a method to analyze the conjunctival image of the eye. This study uses the first-order statistic feature extraction method and K-Nearest Neighbor (K-NN) for classifying the conjunctival image into two conditions, anemia, and non-anemia conditions. The feature extraction method is performed on RGB, Hue, Saturation, Value (HSV), and grayscale color space. The system achieved 71.25% of accuracy by using the most optimal parameters on the Green layer of RGB with K=5 and Euclidean distance equation.

Dimauro et al. [10] aim to identify a procedure for the automatic segmentation and optimization of conjunctiva sections. Therefore, image analysis algorithms have been applied to optimize the area of interest in terms of correlation with the estimated hemoglobin value by blood sampling.

All the related works examined in this study primarily focused on the detection of anemia in humans. No specific research or studies were found that specifically target the detection of anemia in small ruminants. Additionally, no existing literature was identified that establishes an association between the FAMACHA method and an automatic method of anemia detection in small ruminants.

III. Methodology

The methodology proposed in this study consists of five key stages: image acquisition, preprocessing, segmentation, feature extraction, and classification. In this section, each stage is described in detail.

A. Image Acquisition

The image acquisition stage was developed through an Android application, providing users with the convenience of capturing images using just one hand. This feature is particularly advantageous as it allows users to position the animal with their other hand while capturing the image of the conjunctiva. Additionally, the application also offers the option to load images from a file, providing flexibility in the image acquisition process for subsequent analysis. Fig. 2 illustrates the acquisition screen in the application, a green polygon is used to guide the user.

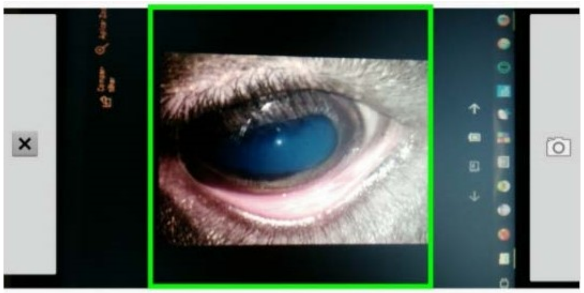

Fig. 2. The screen of image acquisition.

B. Preprocessing

In this stage, the image is prepared for segmentation through the application of detail-smoothing filters and resizing techniques.

The initial preprocessing step involves applying a smoothing filter, specifically a Gaussian filter. This filtering technique helps in the subsequent processes of segmentation by reducing the prominence of image details. It creates a more uniform appearance, making color and texture changes appear more gradual and facilitating subsequent analysis.

Following the smoothing step, the image undergoes cropping and resizing. This phase is essential to optimize the computational efficiency of the feature extraction algorithms.

The image is resized to a resolution of 300 x 300 pixels while maintaining the original aspect ratio. Additionally, a cropping process is applied to retain only the region of interest within the green polygon, which serves as a visual guide for the user during the image acquisition process. This cropping ensures that only the relevant area containing the conjunctiva is preserved.

C. Segmentation

The primary objective of the segmentation process is to accurately extract the region of the animal's conjunctiva from the image. The segmentation process involves the following steps:

1) Conversion of the image color space from RGB to HSV: The image is initially converted from the RGB color space to the HSV color space. This conversion enables better separation and analysis of different color components.

2) Channel separation of the Hue (H) channel: The image is then separated into its individual channels, and the Hue channel is chosen for further processing. The Hue channel tends to highlight the conjunctiva more prominently in most cases, making it suitable for segmentation.

3) Adaptative Thresholding: A thresholding operation is applied to the resulting image from the previous step. This operation converts the image into a binary format, where pixels are classified as either foreground (conjunctiva) or background.

4) Erosion: To eliminate any potential noise or small artifacts in the binary image, an erosion operation is performed. Erosion helps to remove unwanted pixels and refine the shape of the segmented conjunctiva.

5) Generation of a mask: Based on the connected components, a mask is generated to define the region of interest. The mask helps to delineate the boundaries of the conjunctiva accurately.

6) Application of the mask: The generated mask is then applied to the original image, resulting in a cropped image containing only the conjunctiva region. This cropped image is subsequently analyzed for feature extraction and further processing.

Figure 3 illustrates an example of the steps described for the segmentation process.

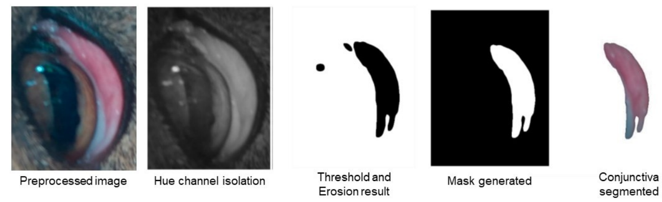

Fig. 3. Example of the stages of the segmentation process.

D. Feature Extraction

In this stage, features were extracted based on the BIC (Border/Interior pixel Classification) descriptor, as well as first-order statistical measures: mean, variance, standard deviation, kurtosis, and skewness.

The BIC (Border/Interior pixel Classification) method was employed to classify each pixel in the image as either belonging to the border or interior region. The algorithm quantizes the color space in 64 different colors. After apply the classification criteria are as follows: Border - If at least one neighboring pixel (4-connectivity) has a different color than the pixel being analyzed; Interior - If all neighboring pixels (4-connectivity) have the same color as the pixel being analyzed. This process allows for the differentiation of pixels based on their spatial relationships and color consistency.

The BIC descriptor generates a compact representation by separating the image data into two histograms: one for the border pixels and another for the interior pixels. Subsequently, these two histograms are concatenated, resulting in a vector that represents the features extracted by the BIC method.

E. Classification

The process of choosing classifiers in a machine learning context, from a given dataset, can be defined as a search activity. The goal is to find, among all the possible algorithms, the one that best describes the learning domain. This search involves exploring and evaluating different classifiers based on their performance and their ability to accurately represent the underlying patterns and relationships in the data. The selection of an appropriate classifier is crucial for achieving optimal results in machine learning tasks, as it directly impacts the model's ability to generalize and make accurate predictions on unseen data.

In this work, we have chosen two classifiers, Support Vector Machine (SVM) and k-Nearest Neighbors (KNN). These classifiers were selected based on their effectiveness in handling classification tasks and their wide applicability in various domains. SVM is known for its ability to handle complex decision boundaries and its robustness against overfitting, making it suitable for both linear and nonlinear classification problems. KNN, on the other hand, is a simple yet powerful algorithm that makes predictions based on the similarity of the input data to its nearest neighbors. By using these two classifiers, we aim to compare their performance and determine which one provides better results.

The parameters of the SVM classifier were estimated using the grid search method provided by the LibSVM package. The grid search allowed us to explore different combinations of parameter values to find the optimal settings for the SVM model. On the other hand, for the KNN classifier, a value of K = 3 was adopted. This means that the KNN algorithm considered the three nearest neighbors to make predictions. The choice of K = 3 was based on empirical observations and previous studies that suggested it as a suitable value for the given dataset and classification task.

IV. Experiments and Results

All experiments and tests were performed using a custom-developed Android application. The application provided a user-friendly interface for capturing and processing images of the conjunctiva. It allowed users to easily capture images using the smartphone's camera or load images from existing files. The application incorporated the entire pipeline of the methodology, including image acquisition, preprocessing, segmentation, feature extraction, and classification. This approach ensured that the experiments were conducted in a real-world, mobile environment, simulating the conditions in which the automated detection of anemia would be performed in practice.

The dataset used in this study was obtained by capturing photographs of real animals. Each animal underwent evaluation based on the FAMACHA scale, and blood samples were taken to determine the hematocrit level. The dataset consists of animals from both species (goats and sheep), exhibiting various stages of infection and distinct coat types. In total, 114 images were analyzed, with 67 images belonging to sheep and 47 images belonging to goats. This diverse dataset enables a comprehensive assessment of the automated detection method across different species and infection stages, enhancing the reliability and generalizability of the findings. Table I shows the dataset distribution.

TABLE I
Dataset distribution.

Species	Healthy	Moderate	Diseased	**Total**
Goats	13	16	18	**47**
Sheep	20	19	28	**67**

The infection levels of the animals were divided into three classes (H, M, and D), with each class corresponding to a range of FAMACHA levels. The healthy class (H) corresponds to levels 1 and 2; the moderate class (M) corresponds to level 3, and the diseased class (D) corresponds to levels 4 and 5.

The hematocrit levels for each class were defined as follows: the D class ranges from 13% (or lower) to 17%; the M class ranges from 18% to 22%, and the H class ranges from 23% to 27% (or higher). This classification scheme allows for the categorization of animals based on their FAMACHA levels and provides corresponding hematocrit ranges that indicate their health status. As can be seen in Table II.

TABLE II
Categorization of classes in relation to FAMACHA and percentage of hematocrit.

Class	FAMACHA	Hematocrit (%)
H	1	>27
	2	23 - 27
M	3	18 - 22
D	4	13 - 17
	5	<17

A total of six experiments were conducted using the two classifiers separately, analyzing both species individually and collectively. This approach allowed for a comprehensive evaluation of the performance of the classifiers in different scenarios.

To analyze the results, three metrics were used: accuracy, recall, and precision. The accuracy metric measured the overall correctness of the classification results, indicating the percentage of correctly classified instances. Recall, also known as sensitivity, assessed the system's ability to correctly identify true positive cases of anemia. Precision, on the other hand, measured the system's ability to accurately classify instances as positive, indicating the proportion of correctly classified positive cases.

The validation set consisted of 17 samples of sheep and 10 samples of goats. These samples were carefully selected to represent a diverse range of cases and ensure a reliable evaluation of the classifiers' performance.

The remaining dataset was used to create the classification models using cross-validation with the k-fold technique, where k was set to 10. This approach allowed for a comprehensive evaluation of the models' performance by repeatedly splitting the data into 10 subsets, using 9 subsets for training and 1 subset for testing. By iteratively rotating the subsets and averaging the results, a more robust and reliable assessment of the classifiers' performance was obtained. The validation set was kept separate from the model creation process.

Table III displays the results obtained during the testing phase of the model construction, while Table IV presents the outcomes achieved using the validation group.

It is worth noting that during the testing phase of the classification model construction, the KNN algorithm achieved better results when analyzing the data from goats. The performance of the KNN classifier in accurately predicting anemia in goats indicates its suitability for this particular species.

TABLE III
RESULTS OBTAINED IN THE TEST STAGE.

Classifier	Species	Accuracy	Recall	Precision
SVM	Goats	0.787	0.750	0.760
SVM	Sheep	0.862	0.862	0.862
SVM	All	0.833	0.745	0.862
KNN	Goats	0.897	0.897	0.897
KNN	Sheep	0.767	0.724	0.710
KNN	All	0.825	0.825	0.825

TABLE IV
RESULTS OBTAINED IN THE VALIDATION SET.

Classifier	Species	Accuracy	Recall	Precision
SVM	Goats	0.600	0.667	0.667
SVM	Sheep	0.760	0.800	0.800
SVM	All	0.740	0.764	0.812
KNN	Goats	0.800	0.833	0.833
KNN	Sheep	0.647	0.667	0.667
KNN	All	0.740	0.750	0.800

Evaluating the results obtained with the validation group, it can be observed that overall, SVM achieved more significant results when analyzing all animals together when compared with KNN. However, when the group of goats is evaluated separately, KNN manages to achieve better results. This indicates that the performance of the classifiers may vary depending on the specific characteristics and patterns present in the data of different animal species. The SVM classifier demonstrates its effectiveness in capturing the overall patterns and trends in the combined dataset, while the KNN classifier shows better adaptability to the distinctive characteristics of goats. These findings highlight the importance of considering the target animal species when selecting an appropriate classifier for anemia detection.

V. CONCLUSION

In conclusion, this study presented an automated method for the detection of anemia in small ruminants through the analysis of the ocular conjunctiva.

The method employed image processing techniques and machine learning to extract relevant features and classify animals into different infection levels. The results obtained demonstrated the effectiveness of the proposed method, with high accuracy, precision, and recall rates. Furthermore, it was highlighted that the choice of classifier (SVM or KNN) had an impact on the results, with SVM performing better in the analysis of all samples combined, while KNN excelled in the specific analysis of goats.

These findings indicate that the developed method has the potential to aid in the early diagnosis and monitoring of anemia in small ruminants.

Future studies could explore the expansion of the dataset and further enhance the performance of the classification model. More sophisticated image classification techniques, such as the use of CNN, can be considered to improve accuracy rates. By continuing to refine and validate this approach, it may ultimately contribute to the improvement of animal health management and welfare in small ruminant populations.

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