Applied Intelligence (2025) 55:536
https://doi.org/10.1007/s10489-025-06398-1

Performance of machine learning methods for cattle identification and recognition from retinal images

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Accepted: 18 February 2025 / Published online: 15 March 2025
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Abstract
Animal identification is a critical issue in terms of security, traceability, and animal health, especially in large-scale livestock enterprises. Traditional methods (such as ear tags and branding) both negatively affect animal welfare and may lead to security vulnerabilities. This study aims to develop a biometric system based on retinal vascular patterns for the identification and recognition of cattle. This system aims to provide a safer and animal welfare-friendly alternative by using image processing techniques instead of traditional device-based methods. In the study, preprocessing, segmentation, feature extraction, and performance evaluation steps were applied for the biometric identification and recognition process using retinal images taken from both eyes. Techniques such as green channel extraction, contrast-limited adaptive histogram equalization, morphological operations, noise filtering, and threshold determination were used in the preprocessing stage. Fuzzy C-means, K-means, and Level-set methods were applied for segmentation, and feature extraction was performed using SIFT, SURF, BRISK, FAST, and HARRIS methods. At the end of the study, the highest accuracy rate was obtained as 95.6% for identification and 87.9% for recognition. In addition, the obtained dataset was shared publicly, thus creating a reusable resource that researchers from different disciplines can use. It was concluded that this study made a significant contribution to the field of biometric-based animal identification and recognition and offered a practically usable solution in terms of animal welfare and safety.

Keywords Biometric identification · Biometric recognition · Retina · Cattle animal · Image processing

1 Introduction

Livestock farming has always maintained its importance as it is a sector in which people trade and obtain many nutrients from past to present. For this sector to be conducted more effectively, the welfare, identification, recognition, and safety of animals are important elements[1]. Biometric identification and recognition in cattle are a key concern in our study, addressing issues like security, theft, and fraud in animal husbandry. Additionally, it significantly influences animal welfare and health. Biometric identification is the process of determining the number of animals you control within a certain animal community. The aim here is to create a system where you can keep information such as whether the animal being identified has been vaccinated, has it had any diseases, and what breed it is. Just as you can now enter the numbers on the ear tags of animals into the automation system and extract their pedigree, in this system you will perform the same operations by scanning the animal's retina. Biometric recognition is the process of determining whether an animal exists in the database. The aim here is to allow you to easily determine which animals belong to you in a large herd.

Cattle are raised in various locations and may be sold before slaughter, which may make it difficult to track their origin. While animal movement affects productivity, it also increases the risk of disease spread, making meat quality suffer [2].

The livestock sector accounts for 20% of global food production and is crucial for food safety, economic growth, and sustainability. However, one of the biggest challenges in this sector is the accurate tracking and verification of animal

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identities. Traditional identification methods, especially ear tags and branding, are both weak in terms of security and can negatively affect animal welfare. Millions of animals are lost every year worldwide, leading to theft, fraud, and false information about genetic information. Studies have shown that animal thefts worldwide cause billions of dollars in losses in the sector. In this context, a stronger system for animal traceability and security has emerged. Biometric identification methods not only provide security but also have the potential to increase efficiency in the livestock sector. The retinal vascular pattern-based identification system developed enables accurate tracking of animals at every stage on farms and large livestock enterprises. This method plays a key role in ensuring food safety by providing farm owners with accurate information about the origins of their animals. In addition, these systems can help prevent the spread of diseases, improve hygiene conditions, and monitor the general health of animals. Especially in markets such as organic and local meat production, the implementation of a reliable and traceable animal identification system will increase consumer confidence and support efficient and sustainable trade in the sector.

Thanks to animal recognition methods, successful results have been achieved in issues such as animal traceability and fraud prevention [3]. The development of animal recognition systems was initiated by different researchers in the late 1960s, and the first results were presented only in 1976 [4]. Until the near future, traditional methods such as ear tags, marking, and branding were used in animal identification. Traditional methods are unreliable for cattle identification as they are vulnerable to theft and fraud. They also harm animal welfare, leading to the search for alternative methods. Among these alternative methods, biometric-based identification systems that do not negatively affect animal welfare and provide more reliable results stand out. Biometric identification technologies based on unique animal characteristics such as face, iris, pattern, muzzle, and retina help prevent problems such as theft and fraud, while also improving the quality of life of animals. For this reason, it is considered an important alternative in the field of animal recognition, replacing traditional methods. Biometric recognition defines an individual's identity, with traits that remain stable unless affected by injury or medical intervention. Biometric features also cannot be replicated identically [5].

This study aims to collect retinal images from cattle and develop an accurate identification and recognition system based on retinal patterns. The identification system determines which animal the retinal image belongs to, while the recognition system checks whether the animal is in the database. To achieve this, the study follows a systematic approach. First, retinal images are collected and preprocessed. Then, vessel segmentation is performed using Fuzzy C-means, K-means, and Level-set methods. For feature extraction from the segmented vessels, the study employs SIFT, SURF, BRISK, FAST, and HARRIS methods. Finally, the performance of the identification and recognition systems is evaluated, and the most successful models are identified. The contributions of this study to literature are as follows:

- To encourage multidisciplinary studies, both the retinal image dataset and the source code developed for this study are publicly shared.
- To determine the most successful approach by measuring the identification and recognition performance of different image processing techniques,
- To compare the performances of Fuzzy C-means, K-means, and Level-set methods in vascular segmentation,
- To compare the success of SIFT, SURF, BRISK, FAST, and HARRIS methods in extracting features from retinas,
- The findings obtained from the study revealed that cattle identification was achieved with 95.6% accuracy and cattle recognition was achieved with 87.9% accuracy.

The study is organized into the following sections: Related studies are presented in Sect. 2, details on the dataset and methods collected within the scope of the study are provided in Sect. 3, experimental results are presented in Sect. 4, the discussion is included in Sect. 5, and the results are presented in Sect. 6.

2 Related studies

Numerous studies have been conducted on the use of biometric features in animal identification, involving different types of animals and biomarkers. However, to our best knowledge, there is no study for an animal recognition system. In the identification system, the tested retinal image is compared with all retinal images in the database, and a match score is obtained. As a result of this match score, if the retinal image with the highest match value and the tested image are the same animal, it is classified correctly. If the tested retinal image and the retinal image with the highest match do not belong to the same animal, it is incorrectly matched. A threshold level is determined in the recognition system. This threshold level shows how much the compared retinal images overlap. When the tested retinal image is compared with other retinas, if the obtained match score is above this threshold level, this animal is labeled as present in the database. If the match score of the tested retina is below the threshold level, this animal is labeled as not present in the database. Studies conducted using retinal images in the literature are summarized below.

Barry et al. collected retinal images of lambs aged between 1 and 22 weeks and examined their matching scores for recognition. In their study, they utilized thirty-eight retinal images taken from both eyes of 19 lambs and employed a regression-based random effects method to obtain matching scores. The average matching score, initially 86% for a lamb of a few weeks old, increased to 96% in subsequent weeks, specifically when the lamb was 8 weeks old [6].

In another study by Barry et al., it was investigated whether the age and breed of sheep caused a difference in retinal imaging. A total of 160 sheep from 4 different sheep breeds (Cheviot, Charollais, Suffolk, and Texel) and two different age groups (< 2 years and > 2 years) were used in the study. In the study, the software of the Optibrand device was used to capture retinal images and match the images. The statistical significance of the results obtained in the study was examined and it was concluded that there was no observable effect of race (P = 0.209) or age groups (P = 0.181) on matching score performance [7].

Allen et al. aimed to recognize cattle in Northern Ireland from the retinal vascular pattern. In the study, a total of 1738 retinal images were taken from both eyes of 869 healthy cattle. In the study, Optibrand software was used to determine the match scores of retinal images. The maximum recognition rate achieved was 98.3% [8].

Barron et al. investigated the effect of light conditions on recognition success in retinal identification. The results obtained indicate that although the average value of the match scores obtained from image pairs taken indoors (95.63 ms) is higher than the average match score obtained from image pairs taken outdoors (89.75 ms), this difference is not high enough to produce statistical significance. Additionally, as a result of the study, single retina-based biometric recognition errors were estimated to be 0.25% for mismatches and 0.82% for non-mismatches[9].

Mustafi et al. developed a system called RetIS for retinal recognition in goats. In the study, it was reported that it was detected with 99% accuracy for more than two hundred retinal images obtained from 12 different goats. In this study, various image processing methods were applied to improve retinal images. One of these is the Contrast Limited Adaptive Histogram Equalization (CLAHE) method. The log-Gabor wavelet method was also used to create the templates [10].

Alturk and Karakus utilized the Optireader device to capture retinal images from both eyes of sixty adult Norduz sheep. In the study, the images of the animals were recorded in the database, and then the matching score was determined for each pair of retinal images to recognize them. An identity was considered correct if the match score was seventy or above. The Pearson correlation coefficient was used to determine the correlation between match scores [11].

Gionfriddo and colleagues conducted a study examining potential changes in the retinas of Beagle dogs as they age. To achieve this, they captured images from both eyes of 18 Beagle dogs of various ages: 1, 3, 5, 7, and 9 years. The findings revealed that retinal vessels tend to narrow as dogs age. However, despite this narrowing, there were no observed alterations in the retinal vascular structure or position [12].

Rojas-Olivares et al. aimed to determine the optimal age at which the retinal vascular pattern can be used for identification and traceability in newborn Ripollesa lambs. In the study, 2534 retinal images were taken from both eyes of 143 lambs from birth to one year of age using Optibrand. A match rate of 70% or more was considered sufficient when matching the retinas of lambs. As a result of the study, it was determined that retinal imaging can be used for the monitoring of 0–12-month-old lambs [13].

When comparing the studies in the literature with this study, one of the most important contributions to the literature is that a unique identification and recognition system has been developed using image processing methods instead of ready-made software, using retinal JPEG images. This approach has increased the accuracy of the system by providing more flexibility, especially in the pre-processing, segmentation, and feature extraction stages of the data. In our study, a larger dataset was created compared to the literature, with 2430 retinal images collected from a total of 300 cattle. Unlike similar studies in literature, the data obtained in this study has been made available to the public. In this way, the reusability of the data has been ensured, and it is aimed to increase multidisciplinary studies by allowing access to researchers from different disciplines.

3 Material and methods

In this study, data collection, preprocessing, segmentation, feature extraction, and feature matching steps were applied for retinal identification and recognition performance assessment in cattle using image processing methods. The flow diagram of the study is presented in Fig. 1.

This study was conducted on a computer equipped with an Intel(R) Core (TM) i7-11800H processor and 16 GB of RAM. Python programming language and the Anaconda Navigator platform were used for coding.

3.1 Collection of retinal images

A total of 2430 retinal images were collected from the right and left eyes of 300 cattle by the authors of this study [14]. The image quality of some of the collected retinal images was unusable for image processing (Fig. 2). Therefore, after a preliminary examination of the images, the identification and recognition system were developed with 1110 retinas of

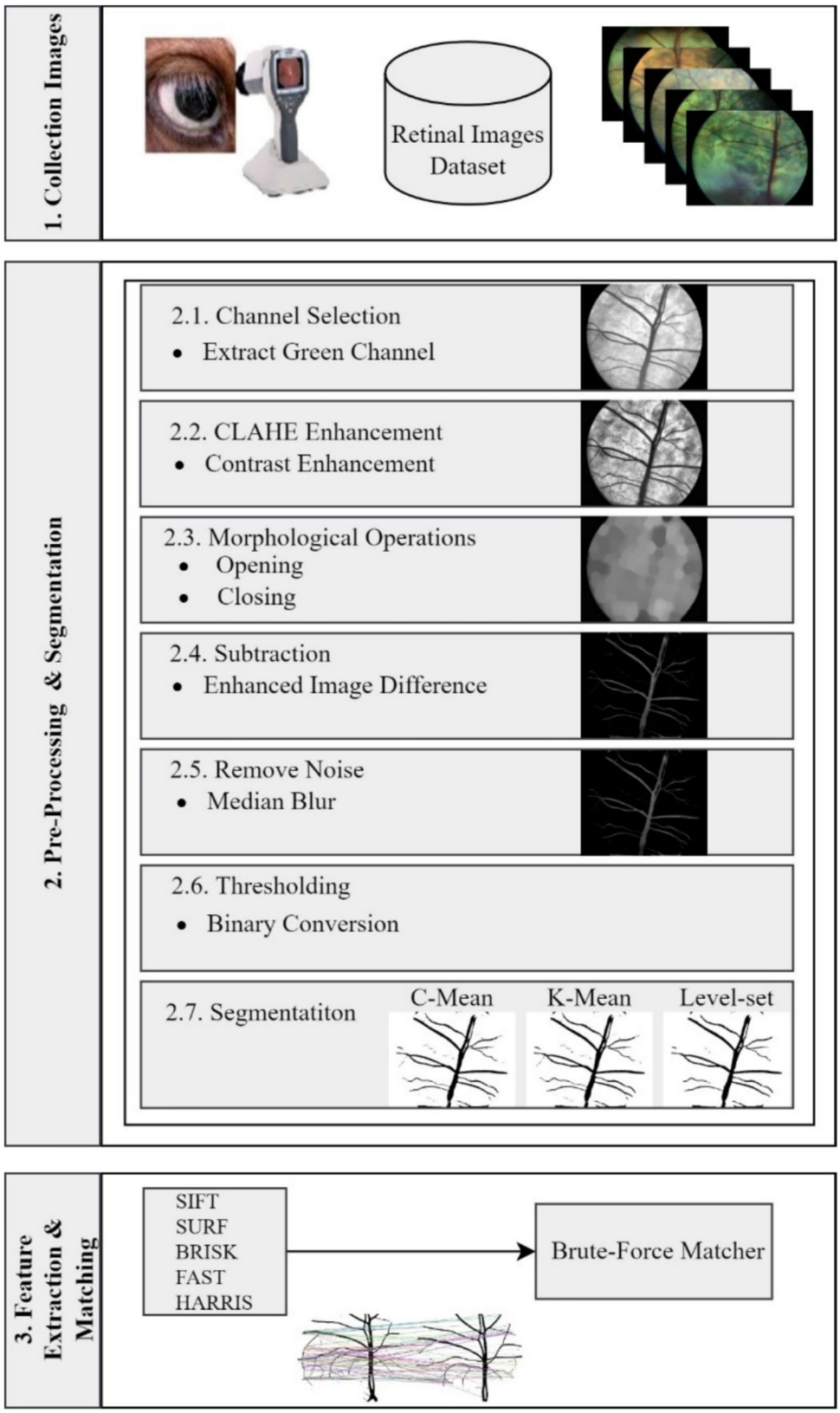


Fig. 1 Flow diagram of the study for cattle retinal identification and recognition

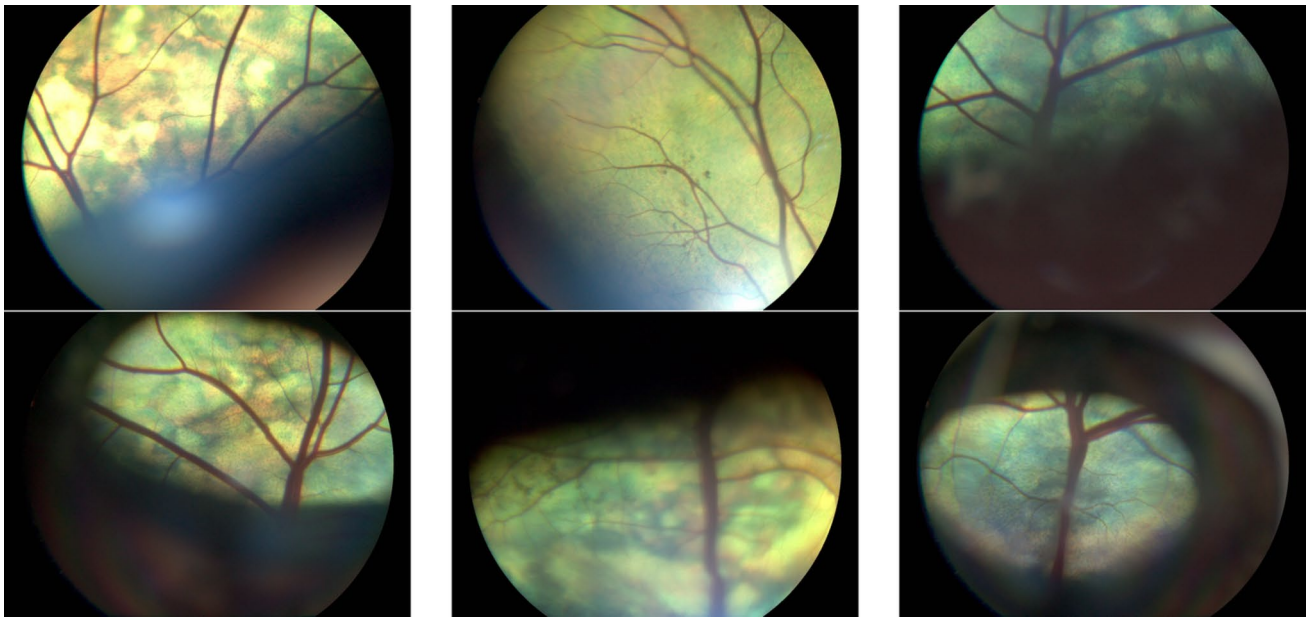


Fig. 2 Example images deleted from the dataset that cannot be used in identification and recognition

good quality (Fig. 3). In this study, 1208 retinal images of 234 cattle were collected by Saygılı and other researchers for the animal identification and recognition system based on retinal images [14].

3.2 Data pre-processing

The pre-processing steps performed in the study include green channel removal, CLAHE, segmentation, morphological operations, image extraction, and noise filtering. Before the pre-processing step, the original size of the images was reduced by fifty percent from 1536×1152 pixels. The purpose of resizing is to reduce the processing time required for each image while maintaining its integrity.

Separating the image into channels and green channel extraction Images consist of three-color channels: red, green, and blue. In this study, green channel extraction was

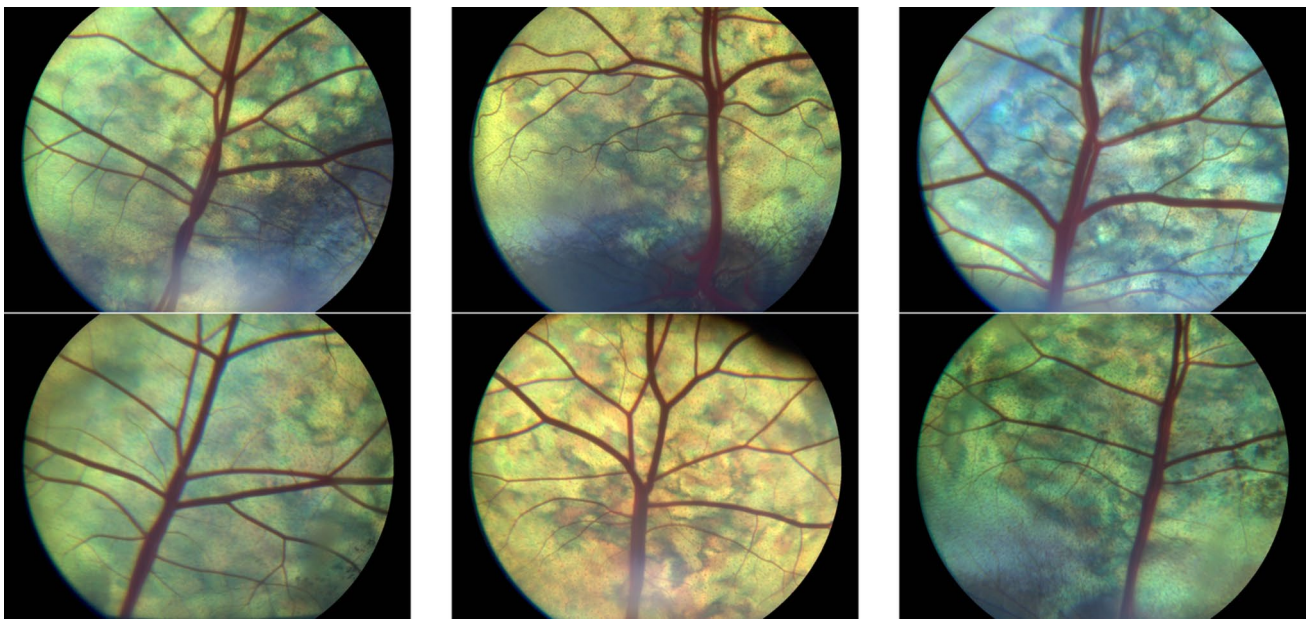


Fig. 3 Sample images in the dataset are used in identification and recognition

first performed to obtain the retinal vascular pattern. The reason for removing the green channel is that the blood vessels have a higher contrast than the other two-color channels. In this way, blood vessels become more visible after green channel extraction is applied[15]. Only the green channel is selected from the original RGB image and used because this channel reveals the vascular structures more clearly than the other channels. By selecting the green channel, the resulting image is transformed into a grayscale image where the brightness of each pixel reflects the green light intensity at that point. This grayscale image makes the vascular structures more visible, allowing the subsequent processing steps to be performed more efficiently.

Contrast limited adaptive histogram equalization (CLAHE) The outstanding feature of the CLAHE method is that, unlike the traditional histogram equalization method, it divides the image into local regions and performs independent histogram equalization operations on these regions. In this way, CLAHE increases overall contrast while preserving details in low-contrast areas [16].

The CLAHE method has two main parameters: clip limit and local region size. The clip boundary clips the intensity peaks at the top of the histogram, while the local region size indicates the size of the separated regions. The clip border parameter affects the performance of the method. When the value is high, the contrast increase is limited, and when the value is low, noise increases. The local region size parameter affects the speed of the method. As the size decreases, the method works slower. The CLAHE method preserves details in low-contrast areas, increases overall contrast, reduces noise, and performs all these operations quickly [17]. For these reasons, CLAHE is a widely used technique in image processing to increase the contrast of images.

Morphological operations Morphological operations were performed on the images obtained after the CLAHE process was applied. Morphological operations are techniques that help distinguish and extract specific components in binary images. These processes include etching and expansion methods. The erosion method works by reducing object dimensions and removing pixels around object boundaries. This also helps reduce noise and irregularities. The expand method adds pixels to object boundaries, expanding their size and filling small holes inside them. Opening and closing operations are combined operations among morphological operations. It is the application of opening, expanding, and then etching processes. Opening softens object contours, removes subtle bumps, and eliminates small holes and gaps in the image. The closing process is the application of etching followed by expansion processes. Occlusion softens contours while focusing primarily on eliminating small holes in objects. These techniques are particularly useful for improving the appearance of binary images, enhancing object shapes, and improving segmentation results [18].

The opening and closing operations were repeated three times using different cores. These repetitions were applied to reduce unwanted noise in the image and make structures more distinct. The opening process helps remove small white particles or spots in retinal images, while the closing process fills in small black holes or voids. Following these procedures, etching was applied to further clarify the retinal details and preserve the fine structures. With the etching process, small objects and noise are reduced by narrowing the white areas in the image.

Subtraction The subtraction operation is applied to separate specified objects from the background in the image. This process is conducted between the image obtained as a result of morphological operations and the image selected with the green channel. Its purpose is to enhance the clarity and visibility of vascular structures in the retina, allowing for sharper and more detailed observation of the vascular patterns.

Noise removal The noise removal stage is frequently used in image processing studies because it produces positive results and increases success. In this process, noise in the image is eliminated while preserving details. The median filter is considered one of the popular noise removal techniques due to its improved mathematical accuracy [19]. For this reason, a median filter was used for noise removal in the study.

Image thresholding Image thresholding is a widely used method in many computer vision and graphics applications. The purpose of thresholding an image is to classify pixels as 'dark' or 'light'. Pixels with lower intensity than the threshold value are marked black, and pixels with higher intensity are marked white [20]. Global thresholding, adaptive thresholding, and Otsu's methods are some of the methods used in threshold determination. Thanks to this thresholding process, a binary image was obtained that effectively highlights the vascular structure.

3.3 Segmentation methods

In this study, three different methods were used to segment retinal vessels. These are Fuzzy C-means, K-means, and Level-set methods. The main motivation for choosing these methods in our study is that they are widely used and provide effective results. These techniques are well-known and reliable methods in segmentation operations and provide sufficient accuracy in our application. In addition, the reason for choosing Fuzzy C-means (FCM), K-means, and Level-set methods is that each method has advantages specific to retinal images. FCM provides high accuracy, especially in retinal images with blurred

boundaries by considering the uncertainties in pixel classification. K-means is ideal for fast segmentation operations in high-resolution images due to its simplicity and speed. Level-set, on the other hand, is a shape-oriented method, capable of precisely determining the boundaries of organic structures such as the retina and can model shape changes well during segmentation. Therefore, these three selected methods provide effective results for retinal image processing and are widely used in this field.

These three segmentation methods were applied to retinal images, the retinal images of each method were presented comparatively (Fig. 8), and their performances were measured (Fig. 10 and Fig. 11). Each of these methods offers a unique approach to segmenting retinal images.

Fuzzy C-means method is an unsupervised method applied in the field of computer vision. Fuzzy C-means is a clustering method that ensures that a piece of data belongs to two or more clusters [21]. It is based on the minimization of the following objective function (Eq. 1).

$$J_m = \sum_{i=1}^{N} \sum u_{i,j}^{m} \|x_i - c_j\| x_i - c_j\|^2 1 \le m < \infty \quad (1)$$

Here m is any real number greater than 1, $u_{i,j,}$ (Eq. 2) is the degree of membership of x_i in cluster j, and x_i is the i^{th} point in the d-dimensional measured data, c_j (Eq. 3) is the d-dimensional center of the cluster and ||*|| are any norms expressing the similarity between any measured data and the center.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (2)$$

$$c_j = \frac{\sum_{i=1}^{N} u_{i,j}^{m} X_i}{\sum_{i=1}^{N} u_{ij}^{m}} \quad (3)$$

The Fuzzy C-means method is implemented by updating the membership of $u_{i,j}$ and cluster centers of c_j through iterative optimization of the objective function shown above.

K-means method is a simple unsupervised method frequently used in clustering problems. The aim is to obtain internally homogeneous and distinct clusters by minimizing the sum of squared distances between data points and their corresponding cluster centers [22]. The steps of the K-means algorithm are as follows:

1. Select the number of clusters, K.
2. Randomly select K points from the data as initial cluster centers.
3. Assign all points to the nearest cluster center.
4. Recalculate the centers of the newly formed clusters.
5. Repeat steps 3 and 4 until a set number of iterations is reached or until there is no change in the cluster centers.

Level-set method is a mathematical technique used to determine the boundaries of an object by changing a function that initially represents a curve or surface over time. This method is especially used in areas such as shape evolution, object tracking, and image processing [23]. The visual version of the level-set method is shown in Fig. 4, and the process steps are given below:

1. Determination of the initial function: An initial function is chosen that represents the boundaries of the object. This function takes negative values inside the object and positive values outside.
2. Evolution of the level-set function: The Level-set function is updated over time. This determines how the object's boundaries change over time.
3. Determination of boundaries: Along the zero level of the level-set function, the boundaries of the object are determined. This shows the evolution of the object's shape.

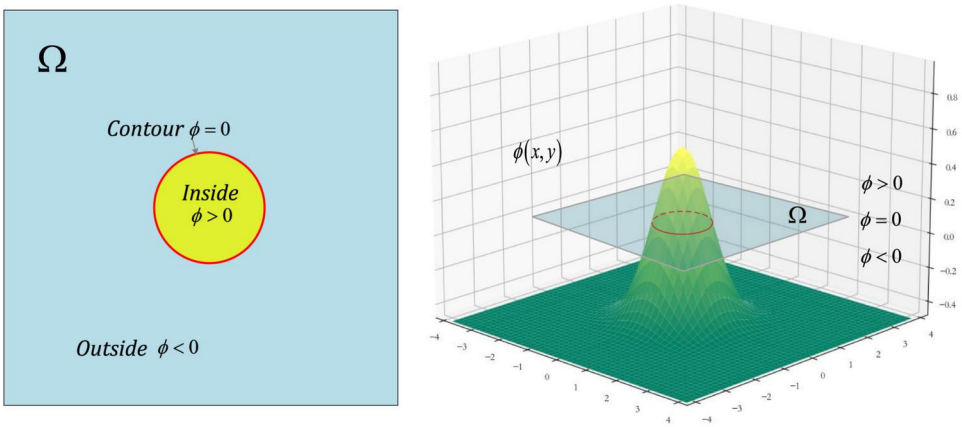


Fig. 4 Illustration of Level-set method [24]

There are many studies on the segmentation of retinal images and detection of blood vessels using Fuzzy C-means[25–29], K-means [30–34] and Level-set [24, 35, 36] methods. However, to our best knowledge, no individual study has employed and comparatively analyzed all three of these methods together. Our study aims to fill this gap in literature.

3.4 Feature extraction methods

SIFT, SURF, BRISK, FAST, and HARRIS methods were used to extract features from retina images.

Introduced scale invariant feature transform (SIFT) algorithm stands out as a prominent tool for detecting and identifying features in images. By automatically abstracting corner points with subpixel precision from a pair of images, this algorithm then represents these points as descriptors, matching them based on the minimum Euclidean distance for the vector [37]. Widely adopted for its ability to extract feature points invariant to translation, rotation, scaling, and illumination changes, SIFT relies on the Difference of Two Gaussians (DoG) operator, an approximation of the Laplacian-of-Gaussian (LoG) operator, to accomplish its tasks [38].

SIFT's methodology revolves around detecting points of interest within a grayscale image, where local gradient direction statistics of image intensities sum up to provide a comprehensive depiction of local image structures surrounding each point of interest. This unique identifier facilitates the matching of corresponding points of interest across different images. Subsequently, the SIFT descriptor found application in diverse tasks such as object categorization, texture classification, image alignment, and biometrics [39].

Speeded Up Robust Features (SURF), offering swift and resilient local representation and comparison of images, the SURF method emerges as an efficient algorithm. Its primary strength lies in its ability to swiftly compute operators utilizing box filters, facilitating real-time functionalities like tracking and object recognition [40]. Comprising four fundamental components, the SURF algorithm includes integral image generation, Hessian detector, descriptor orientation assignment, and descriptor creation. Leveraging integral images with SURF enhances performance significantly. The integral image (I_{Σ}) computation follows Eq. 4.

$$I_{\Sigma}(x,y) = \sum_{i=0}^{i\le x}\sum_{j=0}^{j\le y} I(x,y) \tag{4}$$

Here I is the input image. The time required for the calculation is invariant to change in size. The Hessian matrix is calculated as in Eq. 5.

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \tag{5}$$

L_{xx}, is the convolution of the second-order Gaussian derivative with the image at x = (x, y). L_{yy} and L_{xy} are treated similarly. The matrix determinant serves as a crucial tool for identifying points of interest. Each individual point undergoes comparison with eight points on the local scale, alongside nine points on both the upper and lower scales.

Binary Robust Invariant Scalable Keypoints (BRISK) is a feature extraction algorithm used to detect and identify keypoints in images. Developed as an alternative to algorithms such as SIFT and SURF, BRISK analyzes the image at different resolutions to determine corner points and assigns orientation values to these points according to the brightness changes of surrounding pixels. Binary descriptors of keypoints are created based on pixel brightness differences and these descriptors are compared using Hamming distance. Thanks to its scalable structure, the algorithm accurately detects the same keypoints in objects of varied sizes [41].

Features from Accelerated Segment Test (FAST) is an effective algorithm used to quickly detect corners in computer vision and image processing. Especially preferred for real-time applications, FAST quickly identifies prominent corner points in images. When extracting features from the retina, this algorithm contributes to medical image analysis by detecting important structural features such as vascular junctions or nerve fibers, which are corner points. FAST determines whether a pixel is a corner by evaluating the brightness difference around it and uses the non-maximum suppression method to select the strongest corners [42].

The HARRIS corner detection method is a widely used algorithm for detecting corner points. When used on retinal images, important corners such as the junctions of thin vessels, nerve fibers, and vascular networks can be easily identified. The Harris algorithm calculates the brightness changes around the pixel to create a Harris matrix and calculates an "R" score for each pixel. Using this score, corners, edges, or flat areas are detected; the strongest corners are selected with non-maximum suppression and extracted as features. This method stands out with its speed and accuracy in biometric identification and medical image analysis [43].

3.5 Hyperparameters Tuning

In order to obtain the best results from the methods used in this study, hyperparameter tuning was performed. This process was carried out in two steps. First, a tool was developed to adjust the parameters quickly and easily (Fig. 5).

The method parameters are located at the bottom of this tool and are shown in Fig. 6.

When the buttons next to these parameters are slid, the change in retinal vascular patterns is seen according to the

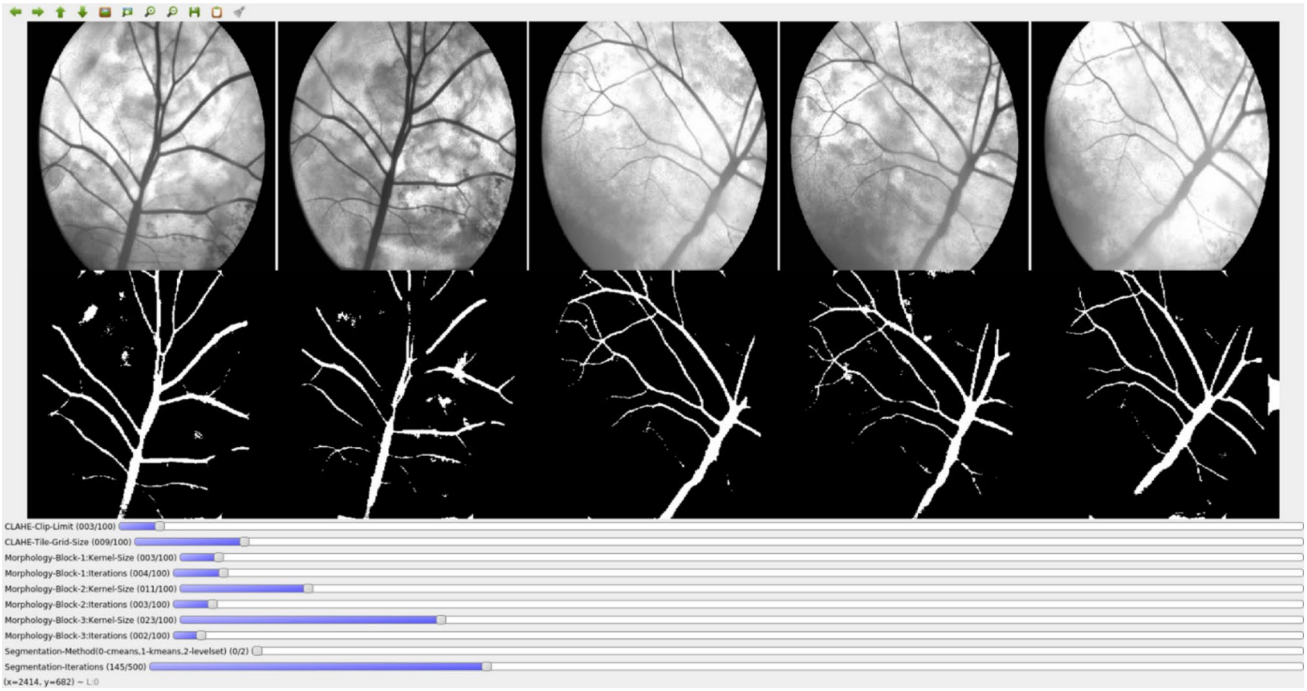
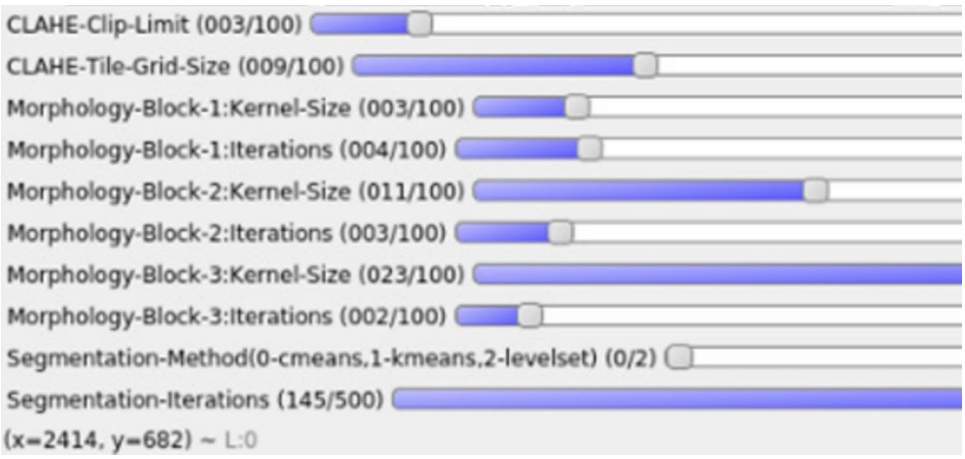


Fig. 5 Tool developed for hyperparameter tuning

Fig. 6 Model parameters and value ranges



values. This change was examined observationally and the parameter values where the vascular patterns were more distinct and the areas outside the vessels were less were selected. As can be seen in Fig. 6, these parameter selections were observed separately by selecting different segmentation methods and the parameters were determined. As can be seen in Fig. 6, the parameters were optimized by selecting 0 for c-means, 1 for kmeans and 2 for levelset. As a result, the parameters and values of the methods used in the study are presented in Table 1.

3.6 Model performance comparison

In this study, matching score and threshold approaches were used to compare the identification and recognition performances of the models. In the matching score approach, the retinal image of the cattle to be identified is compared with the retinal images of all cattle in the database to obtain the match rate. The process performed in this approach aims to identify the animal's ID by examining its retinal image. The Brute-Force matching method was used for calculating

Table 1 Parameter names and values of the methods

Method	Parameter/Value
CLAHE	clipLimit = 2.0 tileGridSize = (9,9)
Median Filter	ksize = 5
Erosion and Dilation	kernel_size = (2,2) / (7,7) / (2,2)
Threshold Determination	threshold = 0.255
Fuzzy C-means	clusters = 2 max_iter = 4
K-means	k = 2 max_iter = 4
Level-set	mu = 0.1 max_iter = 200
SIFT	nfeatures = 0 nOctaveLayers = 30 contrastThreshold = 0.04 edgeThreshold = 1000 sigma = 1.6
SURF	hessianThreshold = 100 nOctaves = 4 OctaveLayers = 30 Extended = False upright = False
BRISK	thresh = 0 octaves = 3 patternScale = 1.0f
FAST	nonmaxSuppression = False threshold = 10
HARRIS	maxCorners = 1000 qualityLevel = 0.01 minDistance = 10 blockSize = 5 k = 4 mask = None

the matching score. The tested retinal image is compared with all other retinal images in the database, and if the best match score belongs to the same animal, it is stated that the recognition has been made correctly.

The feature vectors obtained using SIFT, SURF, BRISK, FAST, and HARRIS are compared with the feature vectors of other retina images in the database using the Brute-Force method and the matching score is calculated. The matching score represents the percentage of overlapping distinctive feature points between the two compared images. It is calculated using the formula in Eq. 6.

$$Matching\ Score = \sqrt{\frac{(matchingPoints)^2}{(pointsImg1) * (pointsImg2)}} \times 100 \tag{6}$$

In this context, "matchingPoints" refers to the count of feature points that have successfully matched between the reference and test images. "pointsImg1" represents the overall number of reliable feature points detected in the reference image, while "pointsImg2" signifies the total number of robust feature points identified in the test image.

In the study, the approach used to evaluate the recognition performance of the models is thresholding. In this approach, an optimal threshold value is determined by analyzing the feature match numbers of correctly matched retinas and incorrectly matched retinas. During the recognition process, animals with a score below the threshold value are not in the database, that is, they are considered unidentified, while animals with a score above the threshold value are in the database, that is, they are considered identified. To determine the optimal threshold value, different threshold values were evaluated. Considering the balance between true positive rate and false positive rate, the value that provides the best performance was determined as the threshold value. After determining the threshold value, FAR (False Acceptance Rate), FRR (False Rejection Rate), Precision, Recall, and Accuracy metrics were used when evaluating the recognition performance of the models. In calculating these metrics, TP (True Positive), FP (False Positive), FN (False Negative), and TN (True Negative) information obtained from the confusion matrix is used.

In this study, the Leave-One-Out Cross-Validation (LOO-CV) method was used to evaluate the model performance. LOO-CV is a widely used cross-validation method. In this approach, each example in the dataset is used as a test set, along with all other data on which the model is trained. The LOO-CV method allows a more reliable assessment of the overall performance of the model because each example is tested in turn and how the model performs on different data subsets is analyzed [44].

In our biometric recognition system, FAR indicates the rate at which a foreign animal, not actually in our database, is incorrectly accepted by the system, meaning it is not included in our animal population. Therefore, the lower the FAR value, the better our ability to detect animals that do not belong to us. In other words, it reflects the reliability of the recognition system. FRR refers to the rate at which an animal within our animal population is rejected by the system, implying the system's rejection of an animal that does belong to us. Similarly to the FAR value, a low FRR value indicates a more sensitive system. Precision indicates how many of the samples a classification model predicts to be positive are positive, representing the ratio of true positive predictions to all positive predictions. High precision suggests few false positives, making the model less likely to generate false alarms. For our study, precision serves as an indicator of how accurately we classify animals that belong to us. Recall (Sensitivity) measures how many true positives are predicted correctly, showing the accurate identification of all existing animals. High sensitivity implies the model doesn't miss true positives and successfully identifies them. Accuracy reflects the proportion of samples that a classification model predicts correctly, indicating the ratio of

correctly predicted animals to the total number of animals. However, accuracy alone might not be suitable for evaluating imbalanced classification problems. The equations for FAR, FRR, precision, recall, and accuracy metrics are provided in Eqs. 7–11, respectively.

$$\text{FAR} : \frac{\text{FP}}{\text{FP} + \text{TN}} \times 100 \tag{7}$$

$$\text{FRR} : \frac{\text{FN}}{\text{FN} + \text{TP}} \times 100 \tag{8}$$

$$\text{Precision} : \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \tag{9}$$

$$\text{Recall} : \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \tag{10}$$

$$\text{Accuracy} : \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \tag{11}$$

4 Experimental results

The cattle identification system based on the retinal vascular model involves several processing steps: data collection, pre-processing (including green channel extraction, CLAHE, morphological operations, and noise removal), retinal vessel segmentation (using Fuzzy C-means, K-means, and Level-set methods), feature extraction (with SIFT, SURF, BRISK, FAST, and HARRIS methods), and performance measurement through matching score and threshold approaches. Figure 7 provides a graphical summary of these steps and sample outputs.

Following pre-processing, vascular structures in retina images were segmented using Fuzzy C-means, K-means, and Level-set methods. The original images (a) and segmented vascular structures (b, c, d) are shown in Fig. 8.

Features from segmented retinal vascular structures were extracted using SIFT, SURF, BRISK, FAST, and HARRIS algorithms, followed by feature matching with the Brute-Force Matcher for recognition. Figure 9 presents sample images with feature-matching results.

In the segmentation step, features from retinal vascular structures, segmented by three different methods, were extracted using SIFT, SURF, BRISK, FAST, and HARRIS algorithms. Identification accuracy was then measured based on match scores, with results shown in Fig. 10.

The identification process measures how accurately each animal's image matches the correct one in the database. If the image with the highest match score belongs to the same animal, it is considered a correct identification. The evaluation results are shown below (Fig. 10):

Fuzzy C-means and K-means segmentation with SIFT and SURF showed the highest accuracy, while BRISK had

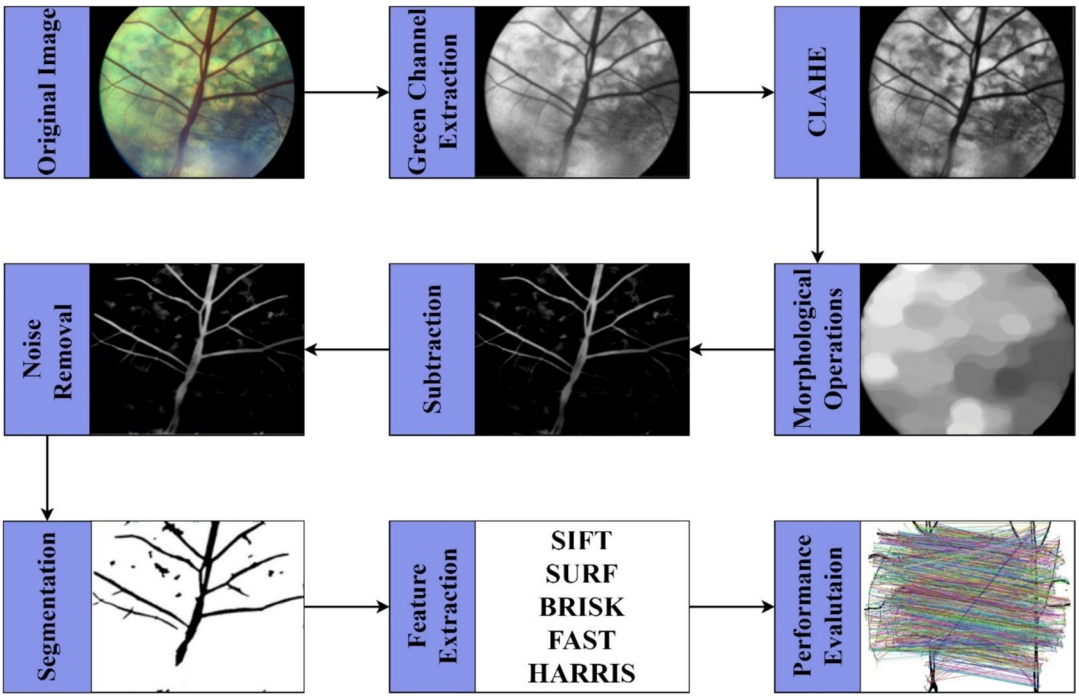


Fig. 7 Process steps of the system and sample outputs obtained

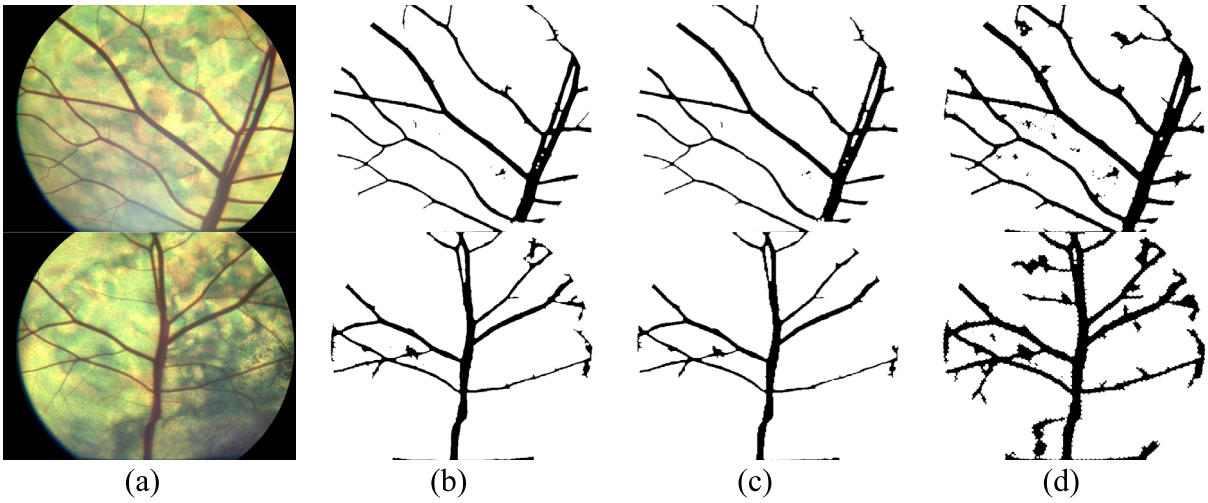


Fig. 8 Original RGB retinal images of cattle (**a**), Fuzzy C-means segmentation (**b**), K-means segmentation (**c**), Level-set segmentation (**d**)

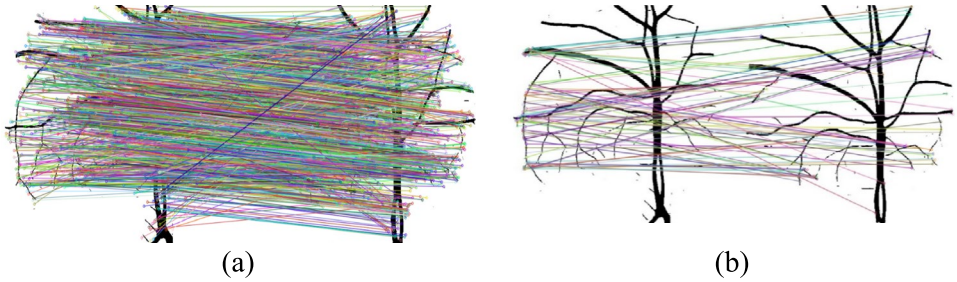


Fig. 9 Highly matching (**a**) and lower matching (**b**) retina pairs as a result of feature matching

lower accuracy (Fuzzy C-means: 0.715, K-means: 0.758). FAST and HARRIS performed moderately with Fuzzy C-means (0.805 and 0.834), and better with K-means (FAST: 0.855, HARRIS: 0.826). Level-set segmentation had the lowest accuracy, but SIFT performed the best (0.908), followed by SURF (0.889) and HARRIS (0.822). BRISK and FAST were least effective with Level-set (BRISK: 0.742, FAST: 0.739). Overall, K-means segmentation paired with SIFT achieved the highest accuracy (95.6%).

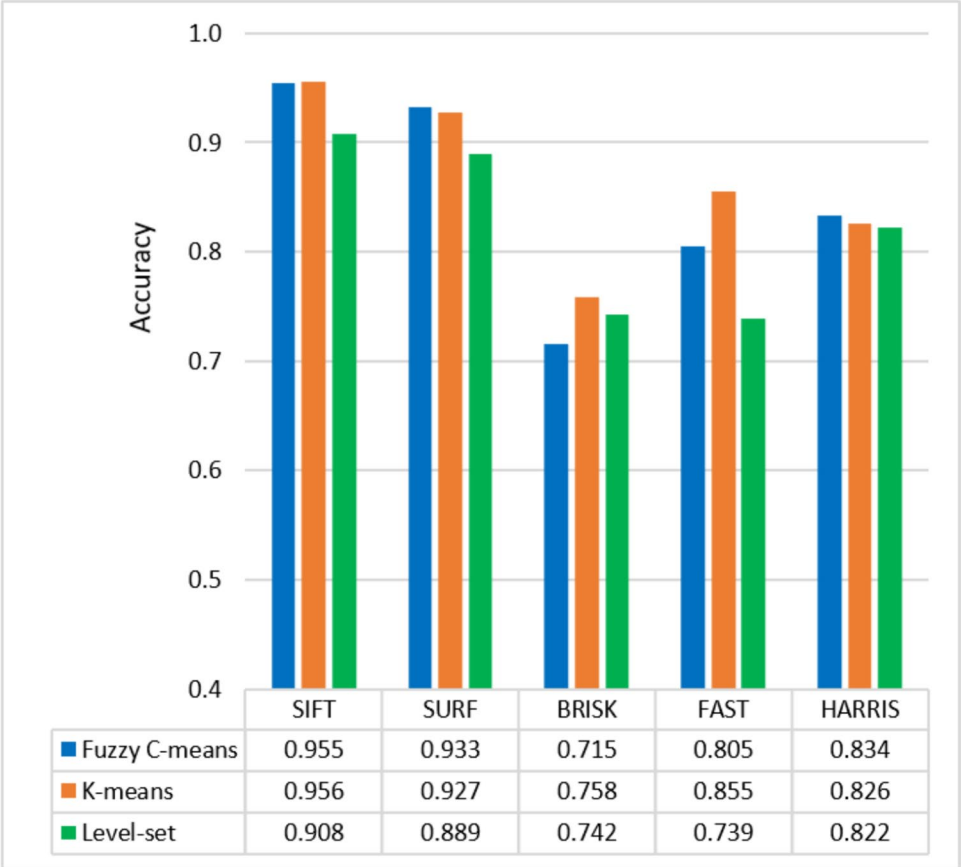
The threshold value in biometric recognition systems is another approach frequently used in the authentication process. One of the most important reasons for its frequent use is that ready-made software is often used in studies in this field and this software recognizes according to threshold values. Therefore, in this study, the performances of the models were tested according to the threshold value approach.

The analysis of feature matching points plays a key role in distinguishing correctly and incorrectly classified retinas. This analysis helps select the optimal threshold value and improves recognition accuracy. The threshold value was selected to optimize FAR and FRR. This balance aims to minimize false positive and false negative results in the system. In this way, recognition accuracy is maximized by setting the threshold value correctly. As a result of the tests, the threshold value was determined as 32.5 for SIFT, 22.5 for SURF, 30.3 for BRISK, 23.6 for FAST, and 37.9 for HARRIS.

In Fig. 11, the performances of segmentation and feature extraction methods are given comparatively according to the threshold values determined for the recognition system.

When the retinal recognition system was implemented, the results in Fig. 11 were obtained and are summarized below:

- SIFT: The best performance was obtained with the Level Set (LS) segmentation method (Accuracy: 87.9%, FAR: 0.120, FRR: 0.120). Both Precision and Recall values are at high levels, which shows that the SIFT method gives the most accurate results after segmentation.
- SURF: It provides the best results with K-Means (KM) segmentation (Accuracy: 85.0%, FAR: 0.150, FRR: 0.127). Although it has lower accuracy than SIFT, it still offers high Precision and Recall values.
- BRISK: It is the method with the lowest accuracy compared to other algorithms. With FCM and LS segmentations, accuracy remained at 71.5% and 74.2%. FAR and FRR values are higher than other methods, which shows that BRISK has low recognition performance.



	SIFT	SURF	BRISK	FAST	HARRIS
Fuzzy C-means	0.955	0.933	0.715	0.805	0.834
K-means	0.956	0.927	0.758	0.855	0.826
Level-set	0.908	0.889	0.742	0.739	0.822

Fig. 10 Identification of the performance of segmentation and feature extraction methods according to the matching score approach

- FAST: It provides the best accuracy (85.5%) with K-Means (KM) segmentation. FAR and FRR values are also at low levels and show moderate success.
- HARRIS: It shows moderate success in general. It reached 82.6% accuracy with K-Means (KM) segmentation. Although its precision value is high, it has a lower accuracy level, especially with LS segmentation.

In general, the most successful combination is obtained with the SIFT feature extraction algorithm and Level Set segmentation method. BRISK shows the lowest performance in all segmentation methods. SURF and FAST show good performance, especially under K-Means segmentation.

5 Discussion

The main purpose of this study is to develop an identification and recognition system in cattle based on image processing and a retinal vascular model. A series of processing steps are needed for this image-processing-based system. Many methods are applied at each step, and it is important to analyze which method is successful and develop the system with the most effective methods. Therefore, after applying a series of pre-processing steps to develop a successful identification and recognition system, three different methods (Fuzzy C-means, K-means, and Level-set) were used for vessel segmentation, and five different methods were used to extract biological features in segmented vessels method (SIFT, SURF, BRISK, FAST, and HARRIS) was used. The performances of these methods were comparatively analyzed. Additionally, in the literature, recognition systems have been created using only the threshold value approach, and identification systems have been implemented using only the match score. In this study, a system that can provide both identification and recognition has been developed.

Figure 12 shows the confusion matrices of the test results of three different segmentation methods of the recognition system (Fuzzy C-means, K-means, and Level-set) and the SIFT, and SURF methods used in feature extraction. In the study, SIFT, SURF, BRISK, FAST, and HARRIS methods were used to extract the features. As seen in Fig. 12, SIFT and SURF methods gave the most successful results according to the accuracy metric.

Figure 12 reveals that the highest recognition accuracy, reaching 87.9%, was achieved when features were extracted using the SIFT method from images segmented with the Level-set method. This approach successfully identified 897 out of 900 animals in the database (true positives),



Fig. 11 Recognition performance of segmentation and feature extraction methods according to the threshold approach

with only 13 animals remaining unrecognized. Furthermore, in vessel segmentation, the Level-set method failed to detect any vessels in only one retinal image, while Fuzzy C-means missed vessels in four images and K-means in six images. From this perspective, the Level-set method appears to be more robust in handling noisy images.

After the experimental results, mismatched retinal images were analyzed. Examples of three different mismatched retinal pairs are provided in Fig. 13. As a result of the analysis, it was concluded that the mismatch occurred due to (i) the appearance of black areas on the retinal image during capturing with the device, where the area outside the retina

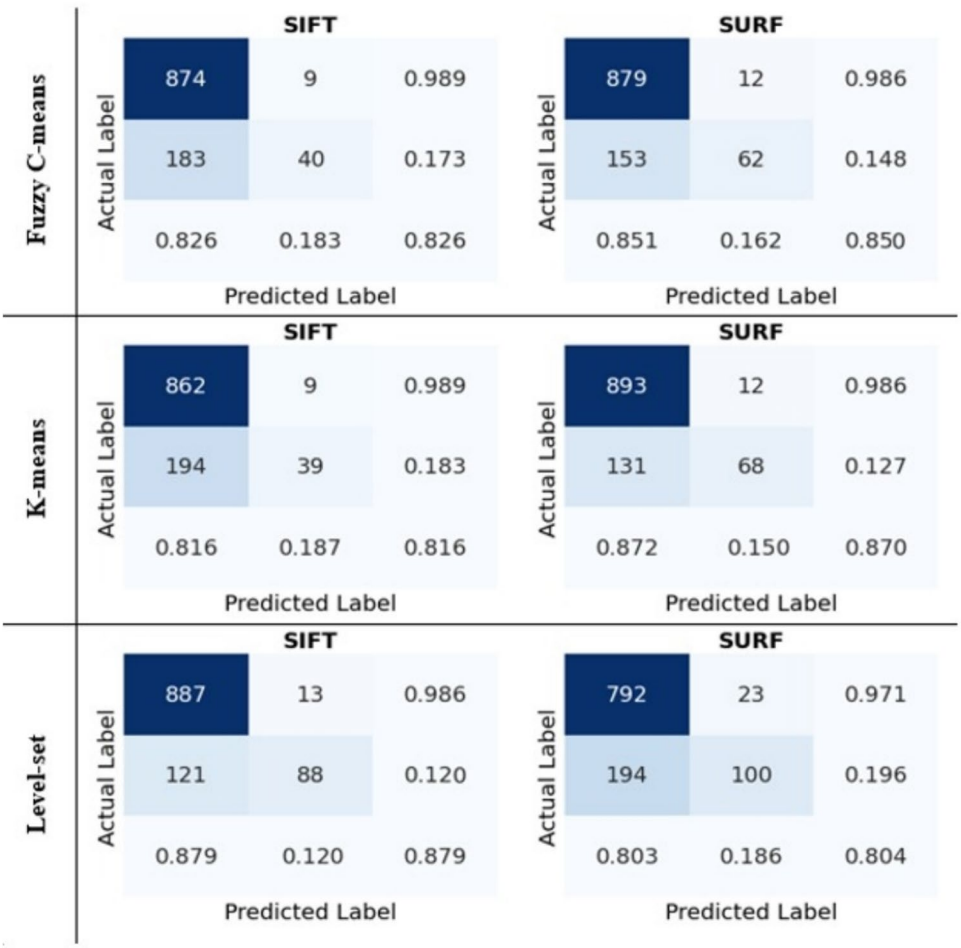


Fig. 12 Confusion matrices of the most successful feature extraction methods in cattle recognition

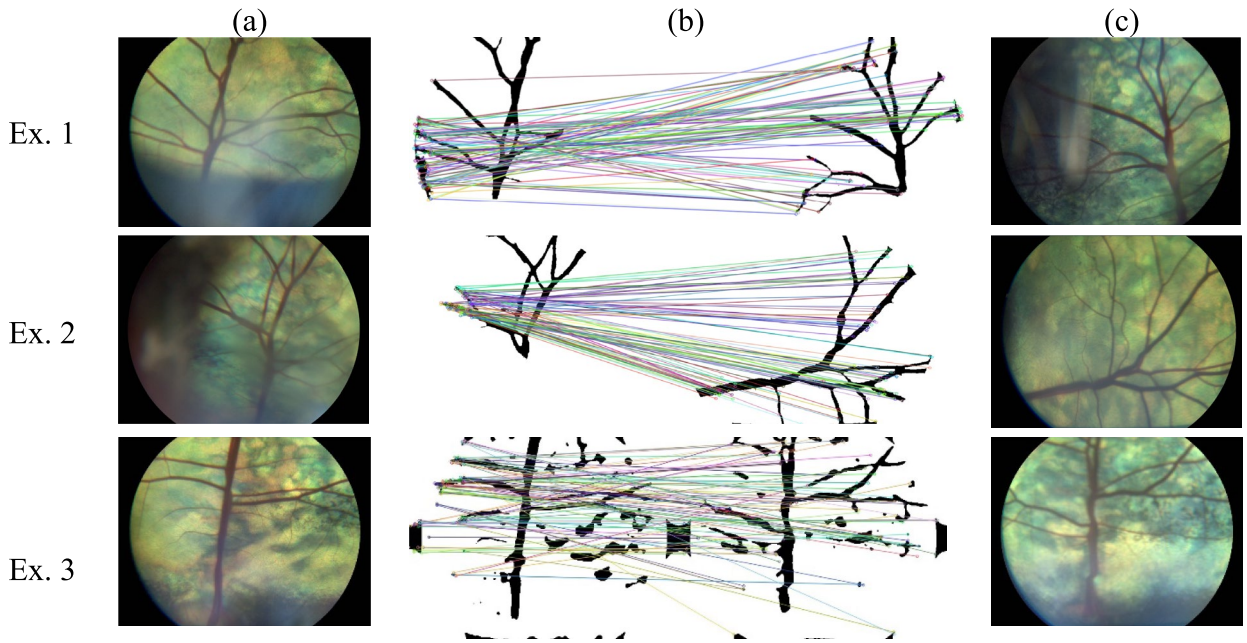


Fig. 13 Tested retinal image (**a**), retinal image matched with the test image (**c**), and matching features of the mismatched retina pair (**b**)

appears black. This area is discarded in the preprocessing step. However, sometimes black areas appear on the retinal image due to shooting errors, leading to incorrect matches (Fig. 13 - Ex. 1). (ii) loss of vascular structure as a result of segmentation (Fig. 13 - Ex. 2), and (iii) matching of tissues without vascular structure (Fig. 13 - Ex. 3).

In studies conducted with animal retina images in the literature, vessel segmentation was generally performed automatically using certain ready-made software. In this study, different methods were used for retinal vessel segmentation and the features of the obtained vessels were extracted with SIFT, SURF, BRISK, FAST, and HARRIS methods. Finally, the match score was used when testing identification performance, and the threshold value approach was used when measuring recognition performance. Table 2 lists the studies conducted with retinal images and the results of this study.

The accuracy value obtained from this study was compared with other retinal image identification studies in the literature (Table 2). The performance of the models varies according to the dataset. Therefore, the most accurate approach will be to compare the methods used in our own dataset and in our own study. Because the structure, number of samples, distribution and features of each dataset differ; therefore, the performance of a method cannot be directly compared with the results in another study or dataset. In this study, the opportunity to determine the most appropriate method was provided by comparing the success of the methods used in their own dataset. In this way, the results obtained provide a more reliable and meaningful evaluation specific to the objectives of the study and the characteristics of the dataset. In our previous study, the identification system was developed with classical image processing methods and 92.5% accuracy was obtained. In this study, it was seen that machine learning methods achieved higher success with 95.6% accuracy. An 87.9% accuracy value was obtained from the recognition system, and there is no study in the literature that we can directly compare. However, it will be possible to emphasize the effectiveness of our study by evaluating the results given in Table 2 from different perspectives.

When Table 2 is examined, it is seen that device-based tools are used in many studies. In our study, image processing techniques were used, which provides independence from device-based tools. This feature offers the advantage of more universal use and hardware independence. For example, in the 2021 study conducted on goats, 99% accuracy was achieved using image processing techniques, but in our study, the identification success rate was 95.6% and the recognition success rate was 87.9% with the image processing techniques used on cattle. This shows the effectiveness of image processing-based methods.

The number of cattle data used in our study (1110 images) is quite high, and when compared to some other studies, it shows that it is strong in terms of data diversity. When we look at the number of animals used in the studies in Table 2, we see that there is only one study with a higher number of animals than our study (1738) and that study was also obtained with device-based tools.

In our study, the identification success rate was obtained with a very high value of 95.6%. This is a very successful result compared to other studies. For example, in the 2008 cattle study, a 96.3% success rate was achieved with device-based tools, but the success rate was quite close with the image processing methods used in our study. In other studies, recognition success rates are often missing or not stated (for example, no recognition was made in sheep studies). This shows that our study offers a successful approach for both identification and recognition, and demonstrates strong performance in both areas.

Table 2 Results of Studies Conducted with Retinal Image

Ref	Year	Animal	#of image	Methods	Identification	Recognition	Success Rate
[6]	2008	Lamb	38	Device-based tools	√	X	96.0%
[7]	2011	Sheep	320	Device-based tools	√	X	Age < 2: 96.16% Age > 2: 96.89%
[8]	2008	Cattle	1738	Device-based tools	√	X	96.3%
[9]	2008	Sheep	128	Device-based tools	√	X	Indoor: 95.63% Outdoor: 89.75%
[10]	2021	Goat	200	Image processing techniques	√	X	99.0%
[11]	2019	Sheep	300	Device-based tools	√	X	Right Eye: 79.87% Left Eye: 89.74%
[12]	2006	Dog	18	Device-based tools	√	X	94.0%
[13]	2012	Sheep	360	Device-based tools	√	X	94.8%
[14]	2024	Cattle	1110	Image processing techniques	√	X	92.5%
Our Study	2025	Cattle	1110	Image processing techniques	√	√	Identification:95.6% Recognition: 87.9%

In some studies, environmental conditions (for example, indoor and outdoor conditions in the sheep study) affected the accuracy rates. However, in our study, the use of image processing techniques provided a more robust solution against environmental factors. While device-based systems can generally be sensitive to environmental conditions, image processing offers a more flexible solution. The fact that the image processing techniques used in our study have a wider application area compared to device-based systems is an important advantage in terms of being able to adapt to different animal species and environmental conditions. This situation enables biometric authentication systems to be more widespread and applicable. As a result, our study has superior features such as achieving high accuracy rates with image processing-based methods, using a large data set, and having high recognition success.

When the dates of identification studies from retinal images in literature are examined, the scarcity of studies conducted in the last five years is striking. It is thought that this is due to the lack of publicly available retinal images, the lack of multidisciplinary studies, and the difficulty in collecting retinal images. However, there are many new studies in literature developed using other biometric methods such as face and nose prints [45–48]. To fill this gap in the literature, the retinal images collected within the scope of the study were shared publicly on Kaggle.

This study's independence from device-based tools enables direct comparability of the methods and results, offering a robust evaluation of the algorithms and techniques used. The findings provide a foundation for developing new approaches and refining existing methods in animal retina image identification and recognition. To advance this field, future studies should explore different datasets and methodologies, thereby enhancing the knowledge and technological capabilities related to retina-based biometric systems.

The lack of ground truth in animal retina images in the literature limits the methods used and affects their performance, causing labeling difficulties. For this reason, it is planned to create a ground truth dataset and share this dataset in future studies. This will enable the use of complex, data-driven approaches such as deep learning, which generally show high performance when fed with large amounts of data. However, these algorithms require sufficient labeled data for training. Therefore, a shared ground truth dataset will allow deep learning methods to be applied effectively in the analysis and classification of animal retina images. Furthermore, the relatively limited use of artificial intelligence and image processing in the veterinary field [49] means that such efforts could open new doors to identifying and understanding previously undetected features and relationships.

6 Conclusion

In this study, a comprehensive image processing-based system has been developed for cattle identification and recognition using retinal images. The system starts with the preprocessing of retinal images and then segmentation of retinal vascular structures is performed using three different segmentation methods (Fuzzy C-means, K-means, and Level-set). Then, features of these vascular structures are extracted by SIFT, SURF, BRISK, FAST, and HARRIS algorithms. A feature-matching score approach is applied to evaluate the identification performance and recognition performance is evaluated by the threshold value approach.

Experimental results show that the identification system achieves a high accuracy rate of 95.6%, while the recognition system achieves an accuracy rate of 87.9%. Regarding segmentation and feature extraction methods, the highest accuracy was obtained by combining K-means segmentation with the SIFT feature extraction method (matching score: 95.6%). The least successful approach in the identification system was achieved by extracting veins using Fuzzy c-means segmentation followed by feature extraction with the BRISK method (matching score: 71.5%). For the recognition system, the best performance was obtained by combining Level-set segmentation with SIFT features (Accuracy: 87.9%, FAR: 0.120, FRR: 0.120, Precision: 0.986, Recall: 0.879). The worst performance in the recognition system was achieved using Fuzzy c-means segmentation combined with the BRISK method (Accuracy: 71.5%, FAR: 0.294, FRR: 0.279, Precision: 0.775, Recall: 0.721). K-means and SIFT provided the highest matching scores by offering the most effective combination for correct identification. On the other hand, the success of the recognition system was more affected by the robustness of Level-set segmentation, which provided higher accuracy despite the noise in the retinal images.

This study highlights the potential of using retinal biometric markers for animal identification and recognition purposes. The findings contribute to advancing the use of retinal image processing techniques in areas such as animal welfare, veterinary practices, and animal husbandry. Furthermore, the use of image processing methods rather than device-based tools allows the methods and results to be more universally applicable and independent of specific hardware configurations. This approach offers the possibility of expanding the use of the system to a wider range of animals and environments, increasing identification and recognition capabilities in a variety of environments.

In conclusion, this study demonstrates the applicability and accuracy of biometric recognition systems based on retinal images in cattle identification and highlights the success of K-means and Level-set methods in feature

extraction with SIFT. The results of this research contribute to the growing field of animal biometric identification and pave the way for future developments in veterinary and animal husbandry applications, especially with the incorporation of new datasets and techniques such as deep learning into the analysis of animal retinal images.

Authors' contributions **PC, AS, MA, NEO:** Study design, writing, drafting, analysis, image processing, and coding. **CSE, UA, AY, OA:** Data collection. All authors reviewed the results and approved the final version of the article.

Funding Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK). This work was supported by the Turkish Scientific and Technical Research Council-TÜBİTAK (Project Number: 121E349).

The open access fee for this study was provided by the open access agreement between TÜBİTAK and SPRINGER.

Data Availability The dataset used in the study is publicly available at https://www.kaggle.com/datasets/animalbiometry/cattle-retinal-fundus-images and the models developed in this study are available at https://github.com/muhammedakyuzlu/cattle-identification-and-recognition.

Declarations

Ethics committee approval The study was approved by the Kafkas University Animal Experiments Local Ethics Committee in Turkey (Protocol number: KAU-HADYEK/2024-123).

Conflict of interest/common interest No conflict of interest or common interest has been declared by the authors.

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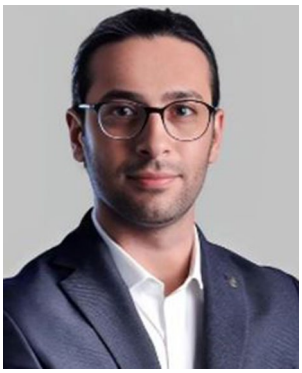
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