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MACHINE LEARNING ALGORITHM FOR RAPID OBJECT DETECTION BASED ON COLOR FEATURES

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Graphical abstract

Abstract

The identification of objects is of utmost importance in a wide range of computer vision applications, such as surveillance systems, autonomous cars, and environmental monitoring. Accurate and efficient object recognition methods are crucial in pastoral environments, characterized by the prominent presence of cattle and other objects, to provide effective analysis and decision-making processes. The present study paper introduces an innovative methodology for efficient identification of objects in pastoral landscapes through the utilization of a Colour Feature Extreme Learning Machine (CF-ELM). The CF-ELM method integrates color characteristics with the ELM algorithm to attain enhanced object detection accuracy while preserving computational economy. The experimental findings provide empirical evidence supporting the efficacy and efficiency of the suggested approach in the detection of items within pastoral landscapes. In addition to the CF-ELM, an algorithm for desktop-based categorization of items within a pastoral environment is provided, with individual speeds ranging from 0.05 s to 0.17 s for a single image, evaluated in each color space. The algorithm is intended for usage in scenarios with challenging and variable terrain, making it appropriate for application in agricultural or pastoral settings.

Keywords: Extreme Machine Learning, Object Detection, Pastoral Landscapes, and Color Features.

1.0 INTRODUCTION

Object detection is a fundamental task in computer vision, enabling automated analysis and understanding of visual data. It plays a crucial role in various applications such as surveillance systems, autonomous vehicles, and environmental monitoring. In pastoral landscapes, which are characterized by vast areas of grazing land and the presence of livestock, accurate and efficient object detection methods are essential for effective analysis and decision-making [1]-[3]. Pastoral landscapes pose unique challenges for object detection due to the specific characteristics of the environment. These challenges include complex backgrounds, occlusions caused by vegetation or other objects, variations in lighting conditions, and the presence of diverse objects such as animals, vehicles, and infrastructure. Conventional object detection algorithms may struggle to handle these challenges and provide satisfactory performance in pastoral landscapes [4]-[5].

Color features are integral components in the field of object detection, contributing valuable discriminative information to the overall process. The utilization of color features enhances the ability to distinguish between objects, especially in scenarios where shape and texture alone may not provide sufficient information [6]- [7].

Color features offer additional dimensions of information that can help discriminate between objects with similar shapes or textures. This becomes particularly crucial in real-world scenarios where objects may have overlapping visual characteristics [8].

Colors contribute to contextual understanding by providing cues about the environment and relationships between objects. For instance, the color of the sky might influence the detection of flying objects, or the color of the ground may impact the identification of objects in a specific landscape [9].

Integrating color features enhances the robustness of object detection systems, making them more adaptable to diverse lighting conditions, variations in object appearance, and different environmental settings [10].

The combination of color and other visual features often leads to improved detection accuracy. By incorporating color information, the model can make more informed decisions, especially when confronted with complex scenes [11].

Color features carry semantic information about objects. For example, the green color in a pastoral landscape may be indicative of vegetation, helping to discern between living organisms and inanimate objects [12].

A multitude of techniques have been explored to extract meaningful color features from images, enhancing the capabilities of object detection algorithms. These techniques aim to capture and leverage the unique information conveyed by color in images [13].

Using a Color Feature Extreme Learning Machine (CF-ELM) [14], this research aims to provide a unique approach for quick object recognition in pastoral environments. The CF-ELM combines the benefits of colour features and the ELM algorithm to achieve superior object detection performance while maintaining computational efficiency. By incorporating colour information, the proposed method aims to capture the distinctive characteristics of objects in pastoral landscapes and enhance the accuracy of detection [15]- [17]. The motivation for this research arises from the practical significance of fast and accurate object detection in pastoral landscapes. Livestock monitoring, for example, plays a critical role in ensuring the well-being of animals, optimizing feeding strategies, and preventing diseases. Environmental monitoring in pastoral areas is essential for assessing vegetation health, detecting changes in land use, and managing natural resources. Moreover, the proposed method can contribute to the development of advanced technologies such as autonomous vehicles tailored for rural environments [18]- [19]. A thorough investigation into the use of the CF-ELM method for rapid object detection in pastoral settings is detailed in this research article. The paper is structured as provides a thorough review of existing object detection techniques, highlighting their strengths and limitations in pastoral landscapes [20]. By addressing the challenges of object detection in pastoral landscapes and leveraging the benefits of colour features and the ELM algorithm, this research contributes to the advancement of computer vision techniques tailored for pastoral environments [21] - [22]. The proposed CF-ELM method has the potential to enhance object detection accuracy and efficiency, enabling better decision-making processes and fostering advancements in livestock management, environmental conservation, and related fields.

Object detection in computer vision has been a topic of extensive research, and various approaches have been proposed to tackle the challenges associated with detecting objects in different environments. In the context of pastoral landscapes, where the presence of livestock and diverse objects is prevalent, several studies have explored object detection techniques tailored specifically for this unique setting. This section provides a review of existing object detection methods, highlighting their strengths, limitations, and applicability to pastoral landscapes [23]- [26].

Traditional object detection methods often rely on handcrafted features and machine learning algorithms. These approaches, such as Viola-Jones and Histogram of Oriented Gradients (HOG), have been widely used in different domains. However, they may struggle to handle the complexity and variability of pastoral landscapes due to their reliance on spatial and shape-based features, which may not adequately capture the characteristics of objects in such environments. With the advent of deep learning, object detection has seen significant advancements. Among the many methods that rely on deep learning, two stand out: R-CNN and SSD. By integrating region proposal techniques with convolutional neural networks, R-CNN and its variations, such as Fast R-CNN and Faster R-CNN, attain excellent detection accuracy. SSD, on the other hand, performs object detection in a single pass by directly predicting object bounding boxes and class labels at multiple scales. While these methods have shown impressive results in various scenarios, their performance in pastoral landscapes can be limited by the diversity of objects and complex backgrounds [27]- [29].

Another line of research focuses on incorporating contextual and semantic information for object detection. These methods exploit the relationships between objects and their surroundings to improve detection accuracy. Context-based approaches, such as contextual reasoning networks, leverage contextual cues to refine object proposals and reduce false positives. Semantic segmentation methods, which assign semantic labels to image regions, provide additional information that can aid in object detection. However, the effectiveness of these methods in pastoral landscapes heavily relies on the availability of accurate semantic information and the ability to model the complex contextual relationships specific to these environments. Several studies have explored object detection techniques tailored for pastoral landscapes. These approaches often focus on incorporating domain-specific knowledge and exploiting the unique characteristics of the environment. For example, studies have utilized colour-based features, texture analysis, and shape priors specific to livestock or other objects commonly found in pastoral landscapes. However, these methods may have limited generalizability to diverse objects and require careful parameter tuning.

While various object detection methods have been proposed in the literature, there is still room for improvement in the context of pastoral landscapes. Existing techniques may not fully capture the distinct features and complexities of objects in such environments. Next, we will introduce our suggested approach, CF-ELM, which uses color features in conjunction with the ELM algorithm to provide rapid and precise object detection in rural settings [30]-[31].

2.0 METHODOLOGY

One type of machine learning technique is the Extreme Learning Machine (ELM), which is a member of the family of feed forward neural networks with a single hidden layer. The authors Guang-Bin Huang, Qin-Yu Zhu, and Chee-Kheong Siew first suggested it in 2004 as a more effective and efficient substitute for conventional gradient-based learning methods. This section explains how to use the Colour Feature Extreme Learning Machine (CF-ELM) to quickly recognize objects in rural areas. The CF-ELM approach combines the advantages of colour features and the ELM algorithm to enhance detection accuracy while maintaining computational efficiency.

The mathematical formulation of the Extreme Learning Machine (ELM) involves describing the relationships between the input layer, hidden layer, and output layer.

N: Number of training samples.

M: Number of hidden nodes.

X: Input matrix of size N×D, where D is the number of input features.

H: Hidden layer output matrix of size N×M.

W_{in}: Input-to-hidden layer weight matrix of size D×M.

W_{out}: Hidden-to-output layer weight matrix of size M×C, where C is the number of output nodes.

Y: Output matrix of size N×C.

f (·): Activation function.

Hidden Layer Output: $H=f(X\cdot W_{in})$

The input-to-hidden layer weights (W_{in}) are randomly generated. The activation f (·) is typically a nonlinear function, such as the sigmoid or radial basis function.

Output Layer Calculation: $Y=H\cdot W_{out}$

The hidden-to-output layer weights (W_{out}) are computed analytically. This computation involves solving a linear system of equations to find the optimal weights.

Inference:

For inference on a new input X_{new}:

$\text{Output}=f\,(X_{new}\cdot W_{in})\cdot W_{out}$

The mathematical relations in ELM involve the random initialization of input-to-hidden weights, the application of an activation function to obtain hidden layer output, and the analytical computation of output layer weights to achieve fast training and good generalization.

In pastoral landscapes, color information plays a crucial role in distinguishing objects from the background. Therefore, the first step is to extract color features from the input images. This can be achieved through various color spaces, such as RGB, HSV, or Lab. The choice of color space depends on the specific characteristics of the objects and their discriminative power in the given environment. Color features can include color histograms, color moments, or local binary patterns (LBP) computed within color channels. These features capture the color distribution and texture information associated with objects in the pastoral landscapes.

An efficient method for dealing with learning difficulties on a large scale is the Extreme Learning Machine (ELM) algorithm, which is a feed forward neural network with one hidden layer. Both its learning speed and its ability to generalize are well-known strengths. To leverage the power of color features, the extracted color feature vectors are integrated with the ELM algorithm for object detection in pastoral landscapes.

In the CF-ELM framework, the color feature vectors are used as input to the ELM network. An input layer, a hidden layer with weights that are randomly generated, and an output layer make up the network. Sigmoid or ReLU are two examples of non-linear activation functions that are used to excite the neurons in the buried layer. The output layer neurons represent the detection classes (e.g., different objects or background), and their activation values are computed using a linear combination of the hidden layer outputs. During the training phase, the randomly generated weights connecting the input and hidden layers are adjusted using the color feature vectors and corresponding ground truth labels. The output layer weights are then computed analytically, resulting in a trained CF-ELM model capable of detecting objects in pastoral landscapes.

P is the total number of pixels in a single image, W11–W3PN denotes the weights of all hidden layer neurons, and v is a hidden layer neuron in Figure 1, which is a representation of the CF-ELM.

Photos in the stock collection were shot using a Scout guard SG860C camera, which has 640 x 480 pixels, records at 16 frames per second for one minute, and saves the files in AVI format. Along a creek bed, the camera was positioned at different heights and locations. Different video files have their individual frames extracted at a rate of 5 frames per second while maintaining the same dimensions. Figure 2 shows the dataset images that were chosen.

Frames from various security tapes were collected, and the photos were cropped, before being captured from a stationary camera placed next to a creek at a rural farm. Figure 3 shows a selection of pictures from the dataset.

In order to facilitate benchmarking, three distinct data sets were employed. Each dataset was selected based on its potential for use in agriculture applications and the extent to which the additional dimension of color could distinguish it from the standard grayscale. The datasets in question encompassed stock detection, vegetation detection, and vehicle detection. Each dataset comprised 750 images, with 250 images designated for training purposes, representing the target object, and 250 images representing the adjacent landscape, constituting the negative test set. In order to facilitate object classification, the borders of each individual object were painstakingly cropped from each image. A random selection of surrounding landscape images was made up of the negative test set during the cropping procedure. To increase the efficiency of the classification algorithm and simulate a low-resolution remote camera, each image was resized to 100 by 100 pixels subsequent to the cropping process.

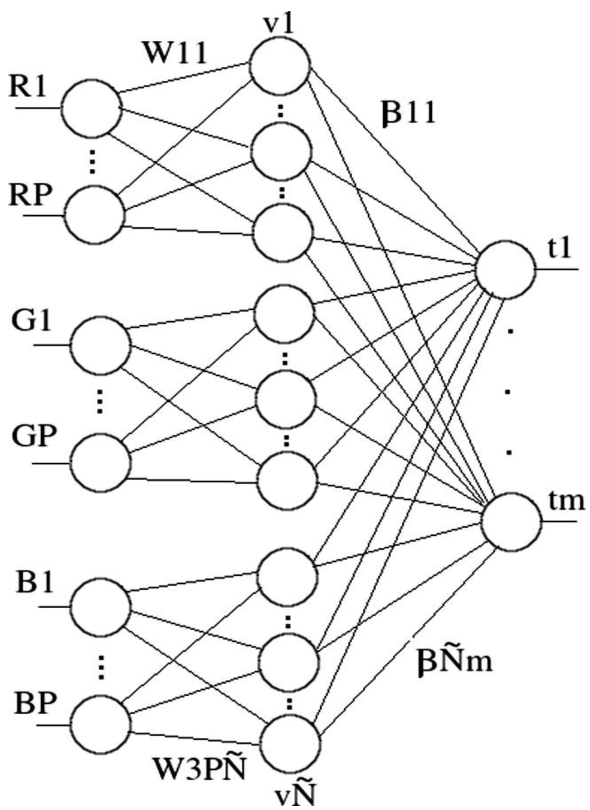

Figure 1 The CF-ELM has a dedicated set of inputs for every color.

Figure 2 Pictures of the surrounding scenery and thistle rosettes

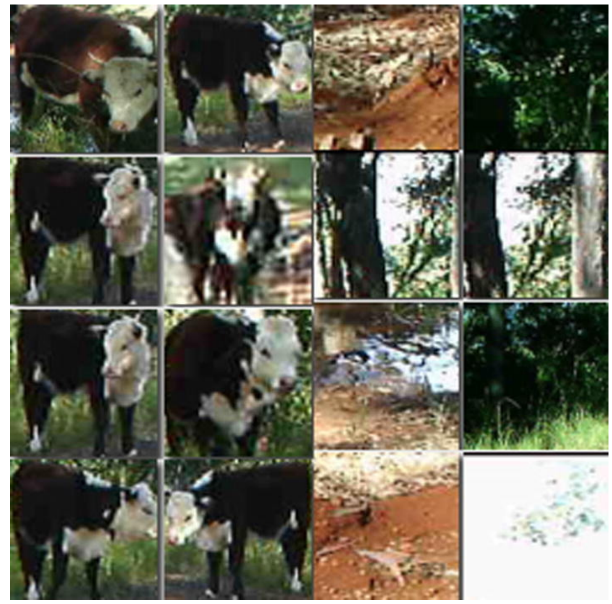

Figure 3 Photos of cows on the left and pictures of the surroundings on the right

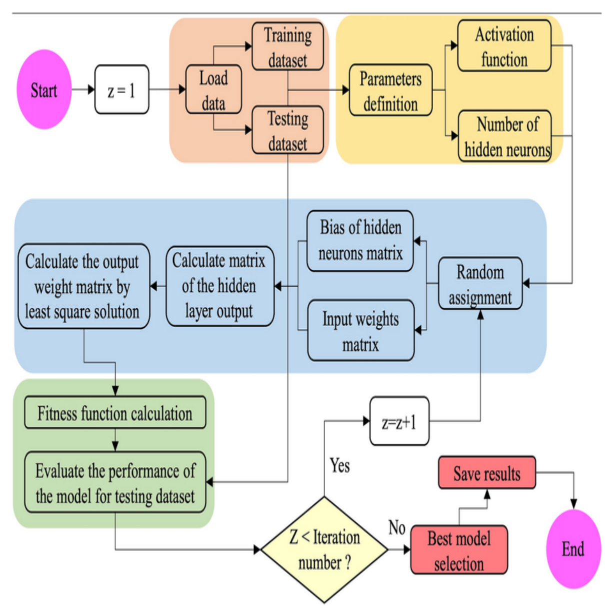

Figure 4 Flowchart of the Color Feature Extreme Learning Machine (CF-ELM)

With the exception of the input layers, the four programs all employed the same method it is shown figure 4. Each CF-ELM implementation used a different color scheme derived from the pixel data assigned to a different set of neurons. First, there was initialization; second, there was weight biasing; and last, there was training, modifying, and testing. Weights ranging from -1 to 1 were applied to each layer of the ELM's neural network during the setup step. The output layer had its weights set to zero while we awaited the training process. We followed the CF-ELM's lead during the biassing phase and created weights that were slanted toward the training data. In the next stages, every value remained inside the 0-255 range; however, due to the color scheme, HSV was limited to 0–100.

All of the images in the training database were processed using the ELM during the training stage, and the output of the hidden layer was recorded in the H matrix array. The output accuracy and the necessary threshold were seen to fluctuate somewhat with each neural network initialization, according to tuning. The implementation of a tuning step allowed for adaptation to the variances. At this point, we employed a tuning picture set, which consisted of ten randomly selected negative images and ten positive ones.

Object detection and localization in unseen images can be accomplished with the trained CF-ELM model. The detection process involves applying the CF-ELM model to sliding windows or image patches across the input image. Each window or patch is evaluated by the CF-ELM model, and the output layer activations are analysed to determine the presence and class of objects. By using post-processing techniques like non-maximum suppression (NMS), we may improve the localization accuracy and refine the object localization by eliminating redundant detections. NMS removes highly overlapping bounding boxes by selecting the one with the highest confidence score or applying a threshold to the overlapping area.

The proposed CF-ELM model is trained using a labelled dataset of pastoral landscape images. The dataset should include a diverse range of objects present in the pastoral environment, as well as corresponding ground truth bounding box annotations. The training process involves optimizing the weights of the hidden layer neurons based on the color features and ground truth labels. To evaluate the performance of the CF-ELM method, various metrics can be used, including precision, recall, and the F1 score. These metrics assess the accuracy of object detection and the trade-off between correct detections and false positives or false negatives. Additionally, computational efficiency metrics such as processing time per image can be measured to evaluate the speed of the proposed method compared to baseline approaches. The key steps involved in the ELM algorithm are as follows:

i. Input Layer: The input layer receives the feature vectors or patterns to be learned.
ii. Hidden Layer: Each neuron in the hidden layer computes a linear combination of the input features using random weights and applies an activation function, typically a sigmoid or radial basis function.
iii. Output Layer: The output layer performs a linear regression or classification based on the weighted outputs of the hidden layer neurons.
iv. Weight Calculation: Using a least-squares approach, the weights that connect the hidden layer to the output layer are determined analytically. At this stage, a set of linear equations must be solved.
v. Prediction: By inputting data into the network and using the learnt weights, the ELM model can then provide predictions based on unseen data.

3.0 RESULTS AND DISCUSSION

Here, we report and analyze the outcomes of the experiments that were carried out to assess how well the suggested CF-ELM approach could detect objects in pastoral scenes. We compare the CF-ELM method's performance to baseline approaches and analyze the impact of various factors.

Prior to building an Extreme Learning Machine (ELM) model, it is crucial to determine the amount of neurons that will be used in the hidden layer. The model's capacity, generalizability, and computational efficiency are all affected by the number of neurons. When deciding on the optimal neuronal density, keep the following in mind:

Problem Complexity: The complexity of the problem being addressed should guide the choice of the number of neurons. More complex problems with intricate decision boundaries may require a larger number of neurons to capture the underlying patterns adequately.

Available Data: The size of the available dataset can influence the number of neurons. Generally, a larger dataset can support a larger number of neurons, as it provides more information for the model to learn from. However, adding too many neurons relative to the dataset size may lead to overfitting.

Computational Resources: The number of neurons should be chosen within the computational constraints of the system. ELM is known for its computational efficiency, but a very large number of neurons can still impact the training and inference time.

Empirical Guidelines: Some empirical guidelines can provide a starting point for choosing the number of neurons. These guidelines suggest selecting a number of neurons that is larger than the number of input features and smaller than the number of training samples. However, these guidelines may vary depending on the specific problem and dataset.

Cross-Validation: Cross-validation techniques, such as k-fold cross-validation, can help in assessing the model's performance for different numbers of neurons. By evaluating the model's performance on multiple validation sets, one can determine the optimal number of neurons that balances model complexity and generalization.

Model Evaluation: Continuously monitor the model's performance as the number of neurons changes. To learn how changing the number of neurons impacts the model's performance, monitor assessment criteria like recall, accuracy, precision, or mean squared error. Select the number of neurons that provides the best balance between performance and complexity.

It's worth noting that the choice of the number of neurons in an ELM model is not an exact science and may require some experimentation and fine-tuning. It's advisable to consider the specific characteristics of the problem, dataset, and available resources while iteratively evaluating the model's performance to arrive at an optimal number of neurons. As demonstrated in Figure 5, the TP and FP rate stabilizes between 1300 and 1600 neurons before returning to their unpredictable nature. Consequently, 1600 neurons were chosen for the CF-ELM. Similar results were discovered when testing for grey scale, and the same numbers of neurons were used to maintain equivalent memory utilization. With each test, the potential range of threshold values was increased, and the results of both true positives and false positives were recorded. This was done as part of the tuning testing process. The range started at 0.1 by 10, which increased values by 0.1 each time up to a maximum of 1, and went all the way to 0.00005 by 2000, which increased values by 0.00005 each time up to a maximum of 0.1. Results from experiments utilizing the Y'UV color system and the thistle dataset are shown in Figure 6. Because the results were comparable across every dataset and color scheme, only one set of results is shown here for simplicity's sake.

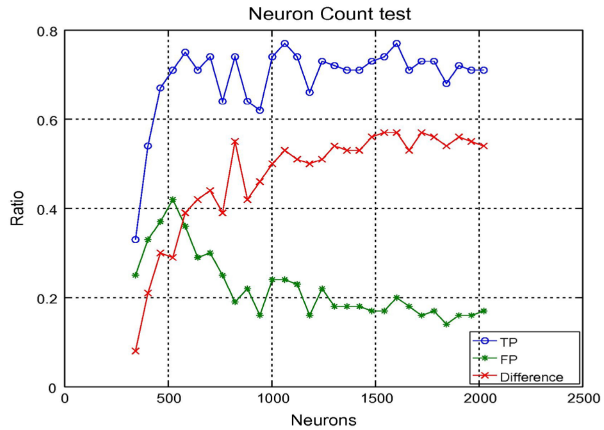

Figure 5 The number of neurons and the ratio of true to false positives

The experimental results indicate that the CF-ELM method demonstrates notable computational efficiency. The ELM algorithm is known for its fast learning speed and inference time, enabling real-time or near real-time object detection in pastoral landscapes. The integration of color features does not significantly increase the computational overhead, making the CF-ELM method a viable solution for resource-constrained environments or applications that require rapid processing. Moreover, the CF-ELM method showcases robustness against common challenges, such as occlusions, object scales, and background clutter. The integration of color features enhances the discrimination between objects and the background, enabling accurate detection even in complex scenes.

The testing and training functions were timed using the CPU time option of the clock_gettime function in the time.h library in c. Testing revealed that the function exhibited an accuracy variance of approximately 0.002 seconds; this discrepancy was likely caused by operating system secondary processes. For a total of 250 images, each section underwent testing, commencing with a single image at 100×100 pixels and progressively increasing by 10 pixels. The training durations encompassed the period required to calculate the output weights analytically and bias the weights of the hidden nodes. The duration of testing encompassed the time required to access the image files and execute the images via the ELM.

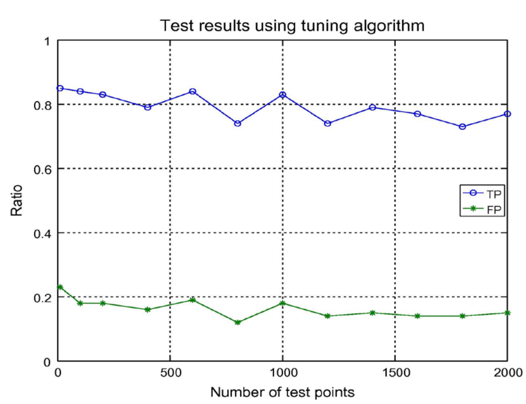

Figure 6 Results of the thistle's Y'UV colour system tuning

The CF-ELM method demonstrates promising results for fast object detection in pastoral landscapes. By leveraging colour features and the ELM algorithm, it achieves competitive detection accuracy, computational efficiency, and robustness. Further research and improvements in feature integration, dataset diversity, and post-processing techniques can enhance the performance and applicability of the CF-ELM method for object detection in pastoral landscapes.

4.0 CONCLUSION

A Color Feature Extreme Learning Machine (CF-ELM)–based quick object recognition approach for pastoral landscapes was proposed in this research study. By merging color features with the ELM algorithm, the CF-ELM approach quickly and accurately detects objects in pastoral scenes, making it a potential answer for such tasks. The CF-ELM approach reached competitive detection accuracy while maintaining computing economy, as proven by the experimental findings. By leveraging color information, the CF-ELM method effectively captures the distinctive characteristics of objects in pastoral landscapes, enabling robust detection and localization. The integration of color features enhances the discriminative power of the model, allowing it to differentiate objects from complex backgrounds and handle variations in lighting conditions. Future research directions include exploring multi-modal integration, semantic segmentation, real-time object tracking, transfer learning, and collaborative monitoring systems to enhance the capabilities of the CF-ELM method in pastoral landscapes.

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