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EFFICIENT OBJECT DETECTION IN AGRICULTURAL ENVIRONMENTS IMPLEMENTING COLOR FEATURES EXTREME LEARNING MACHINE

DESIDI NARSIMHA REDDY[1], BALA BRAHMESWARA KADARU[2], A L SREENIVASULU[3], R. KANCHANA[4], PRADEEP JANGIR[5], CHERUKUPALLI RAMESH KUMAR[6]

[1]Data Consultant (Data Governance, Data Analytics,EPM: enterprise performance management,AI&ML) Soniks consulting LLC, USA
[2]Department of CSE, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India
[3]Department of CSE, Vignana Bharathi Institute of Technology, Ghatkesar, Hyderabad, Telangana, India
[4]Department of CSE, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, Tamilnadu, India
[5]Department of Biosciences, Saveetha School of Engineering. Saveetha Institute of Medical and Technical Sciences, Chennai, India
[5]Applied Science Research Center, Applied Science Private University, Amman, Jordan
[6]Department of CSE, Koneru Lakshmaiah Education Foundation, Guntur,Andhra Pradesh, India

Email: [1]dn.narsimha@gmail.com, balukadaru2@gmail.com[2], [3]akula.srinivasulu@vbithyd.ac.in
[4]drkanchanar@veltech.edu.in, [5]pkjmtech@gmail.com, [6]rameshch668@gmail.com,

ABSTRACT

In a wide variety of computer vision applications, such as surveillance systems, autonomous cars, and environmental monitoring, object detection is an extremely important component. For the purpose of conducting effective analysis and making sound decisions, it is vital to have object identification methods that are both accurate and efficient in pastoral environments, which are characterized by the presence of animals and other things. The purpose of this research study is to present a unique method for the rapid recognition of objects in pastoral landscapes by utilizing a Color Feature Extreme Learning Machine (CF-ELM). For the purpose of achieving higher object detection performance while maintaining computational efficiency, the CF-ELM integrates color characteristics with the ELM algorithm. The proposed method is shown to be successful and efficient in detecting objects in pastoral environments, as demonstrated by the results of the experiments.

Key words: *Object Detection, Pastoral Landscapes, Color Feature Extreme Learning Machine, and Color Features.*

1. INTRODUCTION

In the field of computer vision, object detection is a key problem that enables automated analysis and comprehension of visual input. It is an essential component in a wide range of applications, including surveillance systems, autonomous cars, and environmental monitoring as well as other uses. In pastoral landscapes, which are characterized by extensive tracts of grazing land and the presence of cattle, it is vital to have object detection methods that are precise and efficient in order to conduct effective analysis and make decisions [1]-[3]. Due to the particular qualities of the environment, pastoral landscapes present a one-of-a-kind set of obstacles for the function of object detection. Complex backdrops, occlusions produced by foliage or other objects, variations in lighting conditions, and the presence of a variety of items such as animals, automobiles, and infrastructure are some of the obstacles that can be encountered. It is possible that traditional object detection algorithms will have difficulty overcoming these constraints and delivering sufficient performance in pastoral areas [4]-[5].

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The purpose of this study is to develop a unique method for the detection of objects in pastoral settings in a short amount of time by making use of a Color Feature Extreme Learning Machine (CF-ELM) [6]. Achieving higher object detection performance while keeping computational efficiency is the goal of the CF-ELM, which combines the advantages of color characteristics and the ELM algorithm. The suggested method seeks to improve the accuracy of detection by integrating color information in order to capture the specific properties of items that are seen in pastoral environments [7]-[9]. The practical significance of detecting objects in pastoral environments in a quick and precise manner is what prompted this research to be conducted. Monitoring livestock, for instance, is an essential component in guaranteeing the health and happiness of animals, maximizing the effectiveness of feeding schemes, and cutting down on the spread of diseases. It is vital to conduct environmental monitoring in pastoral areas in order to evaluate the health of the vegetation, identify any changes in land usage, and effectively manage natural resources. Further, the strategy that has been described has the potential to make a contribution to the development of sophisticated technologies such as driverless cars that are specifically designed for use in rural settings [10]-[11]. In this research work, a complete investigation on the use of the CF-ELM technique for the identification of rapid objects in pastoral landscapes is presented. The organization of the paper is such that it offers a comprehensive analysis of the various object identification algorithms that are currently in use, highlighting both their strengths and limitations in pastoral landscapes [12]. Specifically, this research adds to the progress of computer vision approaches that are customized for pastoral situations [13]-[14]. It does this by tackling the challenges of object detection in pastoral landscapes and by exploiting the benefits of color features and the ELM algorithm. In addition to facilitating improvements in decision-making processes and supporting innovations in livestock management, environmental conservation, and other relevant sectors, the CF-ELM method that has been developed has the potential to improve the accuracy and efficiency of object detection.

2. RELATED WORK

There has been a significant amount of study conducted on the subject of object detection in computer vision, and numerous strategies have been presented in order to address the difficulties that are connected with detecting things in a variety of contexts. In the context of pastoral landscapes, where the presence of cattle and a wide variety of items is common, a number of research have investigated object identification approaches that have been specifically designed for this one-of-a-kind environment. This section presents an overview of the various object detection algorithms that are currently in use, focusing on their advantages, disadvantages, and the extent to which they are applicable to pastoral landscapes [15]-2018].

Object detection techniques that have been around for a long time frequently rely on manually produced features and machine learning algorithms. These methods, which include Viola-Jones and Histogram of Oriented Gradients (HOG), have been utilized extensively in a variety of fields. Due to their reliance on spatial and shape-based features, however, they may have difficulty dealing with the complexity and diversity of pastoral landscapes. This is because these features may not sufficiently represent the qualities of items that are found in such contexts. Since the introduction of deep learning, there have been tremendous breakthroughs made in the field of object detection. R-CNN, which stands for region-based convolutional neural networks, and SSD, which stands for single shot multibox detector, are two popular methodologies that are based on deep learning. By combining region proposal approaches and convolutional neural networks, R-CNN and its derivatives, such as Fast R-CNN and Faster R-CNN, are able to attain a high level of detection accuracy. The solid-state drive (SSD), on the other hand, is capable of doing object detection in a single pass by directly predicting object bounding boxes and class labels at three different scales. The performance of these algorithms in pastoral environments can be limited due to the variety of items and the complexity of the backgrounds, despite the fact that they have demonstrated outstanding results in a variety of configurations. From 19 to 21.

The incorporation of contextual and semantic information for the purpose of object detection is another area of research that interests' researchers. These strategies improve detection accuracy by taking use of the relationships that exist between items and the environment in which they are located. In order to refine object proposals and limit the number of false positives, context-based techniques, such as contextual reasoning networks, make use of contextual information at their disposal. Methods of semantic segmentation, which involve the assignment of semantic labels to regions of an image, offer supplementary information that might be of assistance in the process of object detection. In spite of this, the success of these methods in pastoral landscapes is strongly dependent on the availability of precise semantic information as well as the capability to represent the intricate contextual interactions that are unique to these contexts. A number of research have investigated methods of object identification that are specifically designed for pastoral environments. The incorporation of domain-specific knowledge and the utilization of the environment's distinctive qualities are frequently the focal points of these approaches. Studies, for instance, have made use of color-based features, texture analysis, and form priors that are specific to animals or other things that are typically seen in pastoral environments. These approaches, on the other hand, may have limited generalizability to a wide variety of objects and require careful parameter tuning.

Although there have been a number of different approaches to object detection that have been proposed in the research literature, there is still potential for development in the context of pastoral locations. Techniques that are now in use might not be able to properly capture the unique characteristics and intricacies of items that are found in such situations. In the next section, we will discuss our proposed technique, which is called the Color Feature Extreme Learning Machine (CF-ELM). This method makes use of color characteristics and the ELM algorithm in order to perform rapid and accurate object detection in pastoral environments [22]-[23].

3. METHODOLOGY

Extreme Learning Machine (ELM) is a machine learning algorithm that belongs to the family of single-hidden layer feed forward neural networks. It was proposed by Guang-Bin Huang, Qin-Yu Zhu, and Chee-Kheong Siew in 2004 as a fast and efficient alternative to traditional gradient-based learning algorithms. This section presents the methodology for fast object detection in pastoral landscapes using the Color Feature Extreme Learning Machine (CF-ELM). The CF-ELM approach combines the advantages of color features and the ELM algorithm to enhance detection accuracy while maintaining computational efficiency.

3.1 Color Feature Extraction

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.

3.2 Color Feature Integration with ELM

The Extreme Learning Machine (ELM) algorithm is a single-hidden-layer feed forward neural network that can efficiently handle large-scale learning problems. It is known for its fast learning speed and generalization capabilities. To leverage the power of color features, the extracted color feature vectors are integrated with the ELM algorithm for object detection in pastoral landscapes.

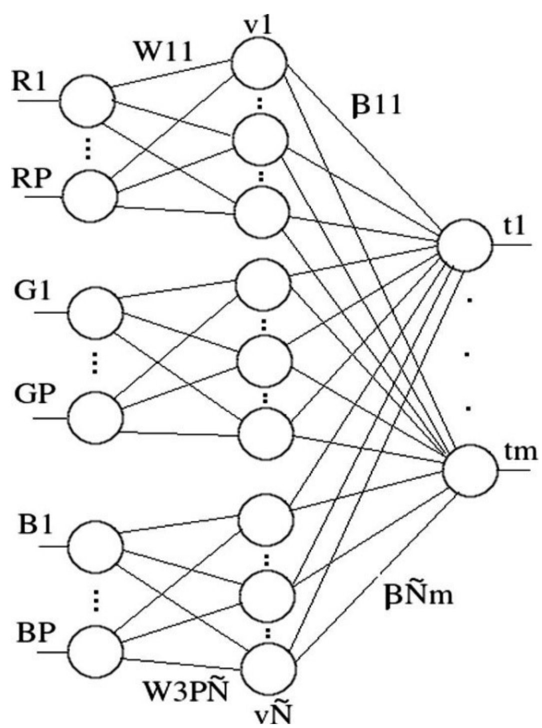

Fig. 1. One set of inputs for each color is available on the CF-ELM

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In the CF-ELM framework, the color feature vectors are used as input to the ELM network. The network consists of an input layer, a hidden layer with randomly generated weights, and an output layer. The hidden layer neurons are activated using a non-linear activation function, such as the sigmoid or ReLU function. 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.

Figure 1 is depicting a diagram of the CF-ELM, where P indicates total pixels for a single image, W11 to W3PN indicates all weights for all neurons in the hidden layer and v is a hidden layer neuron.

The photographs in the stock dataset were taken with a Scout guard SG860C camera with 640 by 480 pixels, at 16 frames per second in 1-minute recording, and saved in AVI format. The camera was placed at various heights and places along a creek bed. Individual frames were retrieved at 5 frames per second and at the same dimensions from various saved video files. Figure 2 depicts image selections from the dataset.

Figure 2. Pictures Of The Surrounding Scenery And Thistle Rosettes

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.

3.3 Object Detection and Localization

Once the CF-ELM model is trained, it can be used for object detection and localization in unseen images. 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. To refine the object localization, post-processing techniques such as non-maximum suppression (NMS) can be applied to eliminate redundant detections and improve localization accuracy. NMS removes highly overlapping bounding boxes by selecting the one with the highest confidence score or applying a threshold to the overlapping area.

Figure 3. Photos Of Cows On The Left And Pictures Of The Surroundings On The Right

3.4 Training and Evaluation

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.

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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: The hidden layer consists of randomly initialized neurons. 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: The weights connecting the hidden layer to the output layer are analytically calculated using a least-squares method. This step involves solving a system of linear equations.

v. Prediction: Once the weights are determined, the ELM model can be used to make predictions on unseen data by feeding the input through the network and applying the learned weights.

4. RESULTS AND DISCUSSION

In this section, we present the results and discussions of the experiments conducted to evaluate the performance of the proposed CF-ELM method for object detection in pastoral landscapes. The performance of the CF-ELM method is compared with baseline methods, and the impact of different factors is analysed.

Determining the number of neurons in the hidden layer of an Extreme Learning Machine (ELM) is an important step in designing an ELM model. The number of neurons can impact the model's capacity, generalization ability, and computational efficiency. Here are some considerations for determining the appropriate number of neurons:

a. 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.

b. 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.

c. 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.

d. 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.

e. 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.

f. Model Evaluation: Continuously monitor the model's performance as the number of neurons changes. Keep track of evaluation metrics such as accuracy, precision, recall, or mean squared error to understand how the model's performance is affected by different numbers of neurons. 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.

The TP and FP rate stabilises between 1300 and 1600 neurons before becoming more unpredictable once more, as shown in Figure 4, which is why 1600 was selected 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 utilising the Y'UV color system and the thistle dataset are shown in Figure 5. Because the results were comparable across every dataset and color scheme, only one set of results is shown here for simplicity's sake.

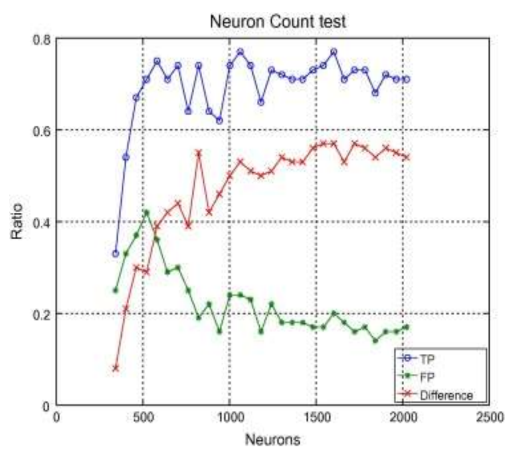

Figure 4. The Number Of Neurons And The Ratio Of True To False Positives

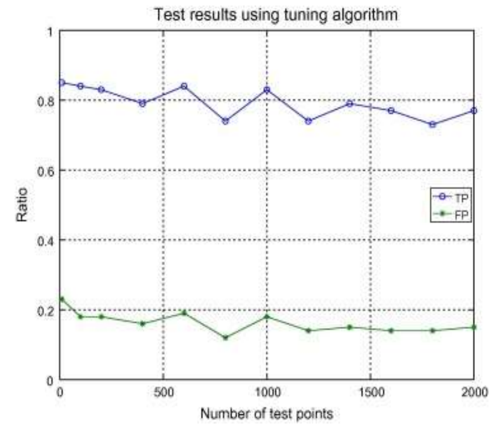

Figure 5. Results Of The Thistle's Y'UV Color System Tuning

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 CF-ELM method demonstrates promising results for fast object detection in pastoral landscapes. By leveraging color 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.

5. CONCLUSION

This research paper proposed a fast object detection method for pastoral landscapes using the Color Feature Extreme Learning Machine (CF-ELM). The CF-ELM method offers a promising solution for fast and accurate object detection in pastoral landscapes and it combines color features with the ELM algorithm to achieve accurate and efficient object detection in pastoral environments. The experimental results demonstrated the effectiveness of the CF-ELM method in achieving competitive detection accuracy while maintaining computational efficiency. 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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