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Su Altı Görüntü Sınıflandırma için HOG Özellik Çıkarıcı ve KNN Tabanlı Bir Yöntem

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Öz

Su altındaki çöpler deniz canlılarının yaşamı ve tüm ekosistemi etkilemektedir. Su altındaki çöplerin tespit edilmesi önemli bir araştırma alanıdır. Bu çalışmada su altındaki çöplerin tespit edilebilmesi için bir yöntem önerilmiştir. Önerilen yöntemin uygulanması için erişime açık Trash-ICRA19 veri seti kullanılmıştır. Veri seti kırpma işlemi uygulanmış ve toplamda 11060 görüntüden oluşan bir veri seti elde edilmiştir. Bu görüntüler ön işleme kullanılarak 200×200 piksele dönüştürülmüştür. Yönlü Gradyan Histogramı (HOG) algoritması uygulanılarak, 11060×900 öznitelik vektörleri elde edilmiştir. Elde edilen öznitelik vektörleri daha sonra KNN (K En Yakın Komşu Algoritması), DT (Karar Ağacı), LD (Linear Discriminant), NB (Naive Bayes) ve SVM (Destek Vektör Makinesi) sınıflandırıcıları kullanılarak sonuçlar hesaplanmıştır. Elde edilen sonuçlar KNN sınıflandırıcının bu yöntemde kullanılması durumunda %97.78 doğruluk elde edilmiştir. Önerilen yöntemde sadece özellik çıkarıcı ve sınıflandırıcı kullanılması, yöntemin hafifsıklet olduğunu göstermektedir. Literatürdeki mevcut çalışmalara kıyasla düşük hesapsal karmaşıklığa sahiptir. Ayrıca performans sonuçlarına göre literatürdeki yöntemlerden başarılıdır.

Anahtar kelimeler: Su altı görüntüleri, HOG algoritması, KNN sınıflandırma, Çöp tespiti

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A HOG Feature Extractor and KNN-Based Method for Underwater Image Classification

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Abstract
Underwater garbage affects the life of marine creatures and the entire ecosystem. Detecting underwater garbage is an important research area. In this study, a method is proposed to detect underwater garbage. The open-access Trash-ICRA19 dataset was used to implement the proposed method. The data set cropping process was applied and a data set consisting of 11060 images in total was obtained. These images were converted to 200×200 pixels using preprocessing. By applying the Directed Gradient Histogram (HOG) algorithm, 11060×900 feature vectors were obtained. The resulting feature vectors were then calculated using KNN (K Nearest Neighbor Algorithm), DT (Decision Tree), LD (Linear Discriminant), NB (Naive Bayes), and SVM (Support Vector Machine) classifiers. The results obtained showed that 97.78% accuracy was obtained when the KNN classifier was used in this method. The use of only feature extractors and classifiers in the proposed method shows that the method is lightweight. It has low computational complexity compared to existing studies in the literature. Moreover, according to its performance results, it is more successful than the methods in the literature.

Keywords: Underwater images, Hog algorithm, KNN classification, Garbage detection

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1. Introduction

The developments in the exploration process of the underwater world; underwater objects, underwater object detection, and classification have become important. There is hardly any place on earth that is not polluted by marine debris. The main source of plastic waste is land, the second source is the seas and oceans. Marine plastics pose a major threat due to their adverse effects on the marine ecosystem and human health. There are many types of garbage found in the seas. However, plastics, one of the most common and harmful marine garbage in every aspect of our lives, are our focus. Disposable plastics (plastic bottles, plastic cups, bags, etc.) are used vulgarly because they are convenient and cost-effective. 1 plastic bag disappears in nature after approximately 1000 years. Despite this, it is estimated that 1-5 trillion plastic bags are used in the world every year. As plastic wastes stay on the seabed, they turn into very small pieces, namely micro-plastics, after passing through various factors. These microplastics cause the death and extinction of living creatures living underwater. This situation not only affects underwater creatures but also affects people quite a lot. Underwater images contain more difficult problems than the land environment. Underwater objects make images blurry and distorted due to problems such as distortion of their shape, color loss, light weakening, and background noise due to prolonged exposure to water. Therefore, these images are more difficult to detect, classify, and obtain a success rate. These difficulties negatively affect the number of scientific studies in these areas due to the high cost of expenses and the wide variety of objects considered sea wrecks. However, recently, developing technology and increasing underwater pollution have increased such studies. Current studies on garbage and sea creatures in the literature are summarized in Table 1.

Table 1. Summary of studies in the literature

Author	Year	Class	Number of Images	Method	Accuracy (%)
Fulton et al. [1]	2019	Tash, bio, and Rov	5720	Faster RCNN	%81
Han et al. [2]	2020	Sea cucumber, sea urchin, and scallop	30000	Faster RCNN	%90
Li et al. [3]	2020	Bottle, bag, and Styrofoam	1505	YoloV3	%91.43
Tata et al. [4]	2021	Plastic	3200	YoloV5	%85
Rosli et al. [5]	2021	Jellyfish, big fish, small fish, crab, shrimp, and starfish	14518	YoloV4	%97.96
Wu et al. [6]	2022	Garbage, living, and underwater robot	7.684	YoloV5	%97.5
Li et al. [7]	2022	Jellyfish, big fish, small fish, crab, shrimp, and starfish	25612	YoloV4	%75
Moorton et al. [8]	2022	Jellyfish, fish, starfish, shell, net, mask, cardboard, plastic, bag, and plastic sheet	1744	CNN	%89
Demir et al. [9]	2022	Small size plastic bottles, large plastic bottles, glass bottles, and packaging	720	YoloV4	%88.7

When current studies are examined, artificial intelligence-based methods have been developed for underwater images and classification has been made. Generally, Yolo [3] and CNN [2] based methods are preferred. Underwater robot [5] technology is used for underwater imaging. Detection of sea creatures and garbage detection were made by using an underwater robot. As sea creatures; Vivid images of sea cucumbers, sea urchins, scallops, jellyfish, big fish, small fish, crabs, shrimp, and starfish were used. In the garbage category, images consisting of metal, plastic, cardboard, and glass objects were used. When the studies in the literature are examined, studies have generally been carried out for the detection of sea creatures [8] or garbage objects [9]. Han et al. [2] proposed a CNN-based method for detecting sea creatures (sea cucumber, sea urchin, and scallop) in underwater images. In the proposed method, only sea creature images were taken into account. No results were obtained for garbage images. Tata et al. [4] presented a method based on YoloV5 by obtaining plastic images with an underwater robot. 3200 images were used and plastic images were examined. Rosli et al. [5] proposed a yoloV4-based method for detecting jellyfish, big fish, small fish, crabs, shrimp, and starfish using an underwater robot. Rosli et al. [5] In the data set they used, many classes of sea creatures can be detected, but there is no garbage object in the data set. There are only images of sea creatures.

In this study, a Trash-ICRA19 hybrid (garbage, sea creature, and rov) dataset is used, which is designed to find all plastic debris with a large dataset of underwater images and to separate the remains from biological assets and intentionally placed man-made objects [1].
In the literature, the most commonly used image enhancement techniques are histogram equalization [10] and contrast spreading [11]. In addition, the improvement algorithm based on Empirical Mode Decomposition (AKA) and wavelet noise removal method [12], adaptive smoothing techniques, and some filtering methods such as anisotropic filtering and homomorphic filtering [13] are also suggested. In this study, the histogram equalization method was used. 11060×900 feature vectors were obtained. These features are classified by the KNN algorithm. Our motivation is to propose a new inference model to achieve a high rate of classification and detection.

2. Materials and Methods

This application is developed on the MATLAB 2020a programming language platform. The steps of the application developed in this section are given below step by step. The general steps of the proposed model are:
Step 0: Crop the Trash-ICRA19 images.
Step 1: Preprocess the cropped images.
Step 2: Obtain feature vectors with the Hog Algorithm.
Step 3: Classify features using a decision tree, support vector machine, linear discriminant, naive Bayes, and k nearest neighbor algorithms.
The flow diagram of the model is shown in Figure 1.

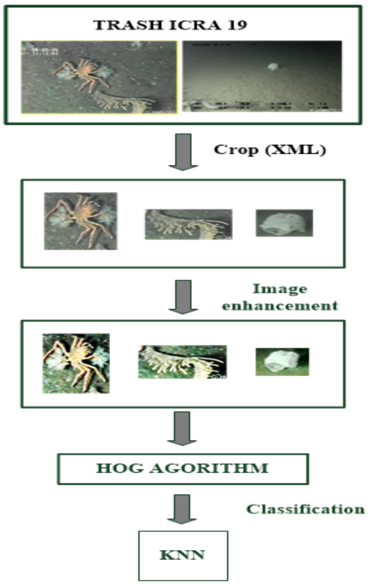

Figure 1. Graphical summary of the proposed method

2.1. Dataset preparation

The trash-ICRA19 dataset was used in this study. This data set; includes three parts: training (75%), testing (15%), and validation (10%). The Trash-ICRA19 dataset has a resolution of 480 × 360 pixels. This dataset has 7684 images; It consists of 3 different classes: bio (all natural biological materials including fish), plastic (marine waste, all plastic materials), and rov (remote-controlled underwater vehicle). An object in each image was obtained by extracting the coordinates of the objects from the XML files of the Trash-ICRA19 dataset and cropping it. Thus, a new data set with different dimensions, with the number of images increased to

11060, was created. The class names of the Trash-ICRA19 data set and the number of objects belonging to each class are shown in Table 2.

Table 2. Class names and number of objects belonging to each class

Class Name	Number of Objects
Bio	2417
Plastic	6339
Rov	2274
Aggregate	11060

2.2. Preprocessing

The second stage of the proposed model is preprocessing. Image enhancement should be done to improve image quality, compensate for attenuation effects, adjust color, reduce noise and blur, and high accuracy. Using the image histogram, the histogram equalization method, which is an image enhancement method, has been applied to the images whose color values are not uniformly distributed. The image needs resizing to avoid any later problems. The image can be any size. The image needs to be set to a constant width and height ratio. Images with different sizes were resized to 200 × 200. Example image enhancement images are shown in Figure 2.

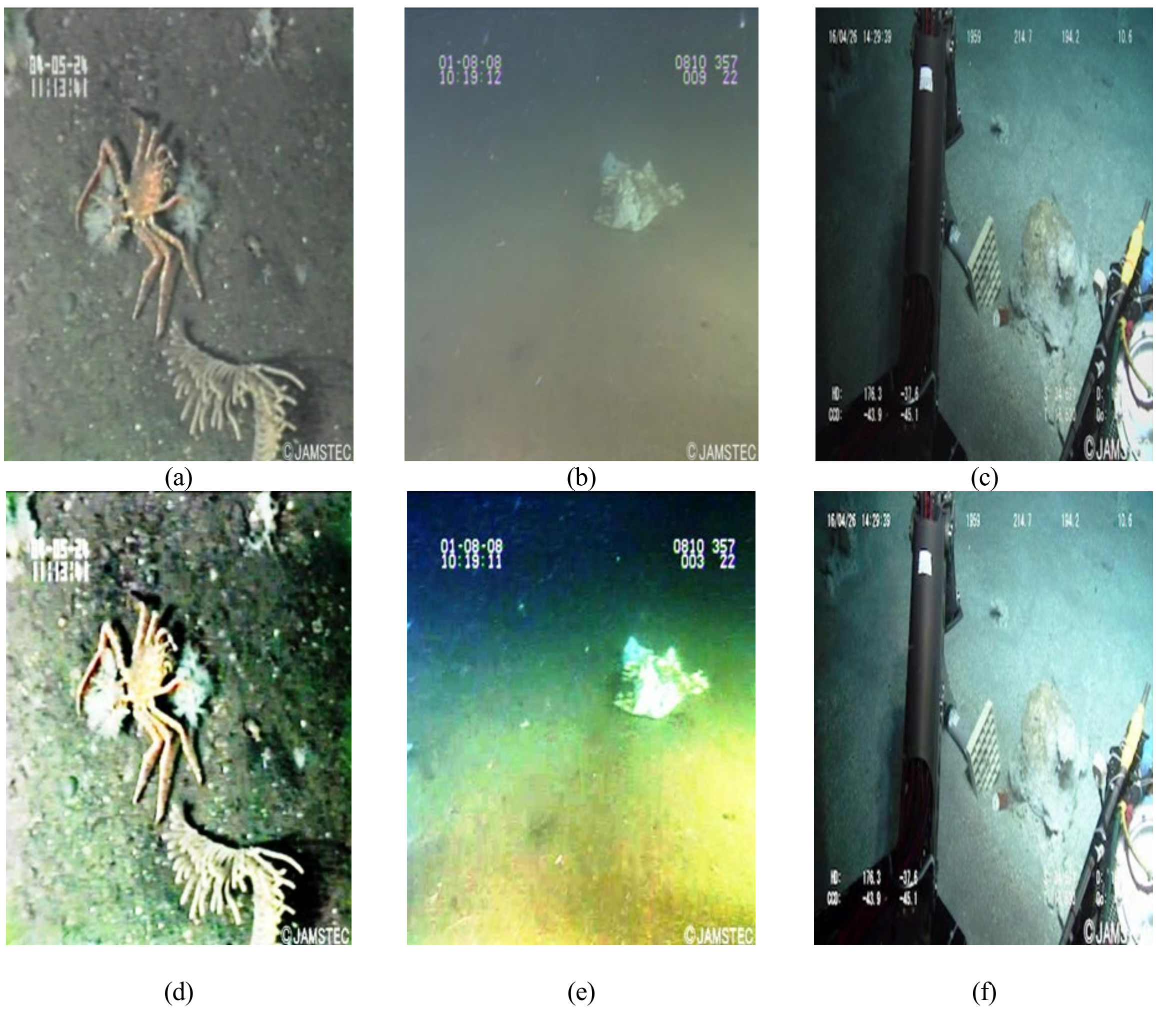

Figure 2. Image preprocessing of sample underwater images. (a,b,c) Sample images from TrashIcra dataset, (d,e,f) Images obtained using image preprocessing

Average pooling is one of the pooling techniques generally used in CNN models. The pooling layer is mostly applied to feature matrices. In Figure 3, if a 4x4 feature matrix is applied and a 2x2 average pooling is applied, the 2x2 matrix on the right is formed. For this reason, it includes the calculation of the average for each section with the Average pooling method. The purpose of the pooling method is to reduce dimensionality. Thus, both the required processing power is reduced and the unnecessary features are ignored and the most important features are focused on. In this study, images are reduced to 200×200 pixels and 50×50 pixels with the average polling process.

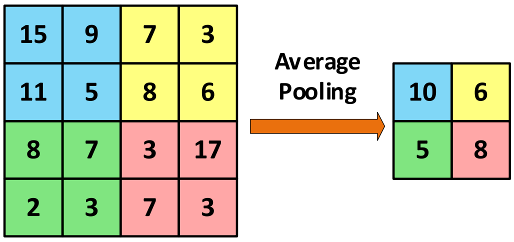

Figure 3. Average pooling process

2.3. HOG feature extractor

The use of HOG was first suggested by Shashua [14] and Dalal [15]. The main goal of the HOG method is to define the image as a group of local histograms. These groups are histograms in which the magnitudes of the gradients are summed. To extract the HOG values of an image, firstly, the horizontal and vertical Sobel filters of the image are applied, and the edges, Ix and Iy, are determined. It then calculates the gradient and their orientation angles using Ix and Iy with the Sobel filter applied. The block diagram of the HOG algorithm is shown in Figure 4.

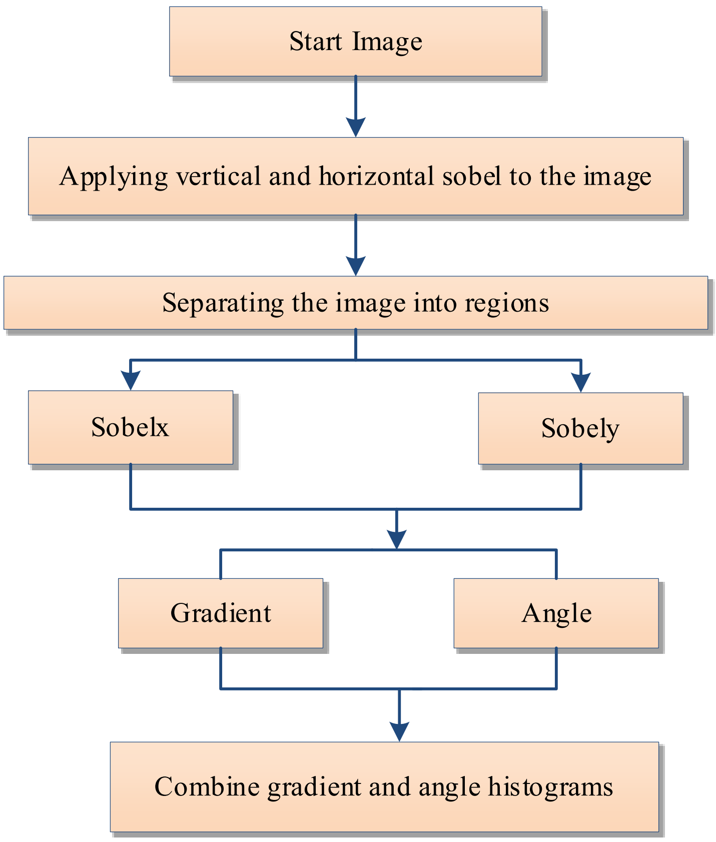

Figure 4. HOG algorithm flowchart

11060×900 feature vectors were obtained by applying the Directional Gradient Histogram (HOG) algorithm, which is one of the methods sensitive to image texture.

2.4. Classification

The features obtained as a result of feature selection algorithms are classified by Decision Tree, Linear Discriminant, Naïve Bayes, Support Vector Machine, and KNN algorithms. KNN is one of the simplest Machine Learning algorithms based on the Supervised Learning technique. It is used to solve classification and regression problems. In the KNN algorithm, the training set is first created. Then the K value and a distance function are selected. When new data is encountered, the distance of this data to the data in the training set is calculated one by one using the selected distance algorithm [16] KNN runs the distance formulas to calculate the distance between each data point and the test data. The parameters of the KNN algorithm used in the proposed method are shown in Table 3.

Table 3. Parameters of the KNN algorithm used in the proposed method

Parameters	Values
Number of neighbors	1
Distance metric	City block

3. Experimental Results

The experiments presented in this section were conducted on a computer equipped with a 64-bit Windows® 10 operating system, a 16-core Intel i7-7200U processor with 64 GB of RAM, and a clock speed of 2.8 GHz. Accuracy, precision, and recall were selected to comprehensively calculate performance. These performance metrics were calculated using the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). The mathematical expressions of the performance measures used are shown in equations 1-3. [17]-[18] .

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

DT, KNN, SVM, NB, and LD classification algorithms were used to classify the selected features. Classification results were obtained using the MATLAB Classification Learner Toolbox. 10-fold cross-validation was chosen as a validation technique to obtain the best results. A comparison of accuracy results with other classifiers (DT: Decision Tree, LD: Linear Discriminant, NB: Naïve Bayes, SVM: Support Vector Machine, KNN: K Nearest Neighbor Algorithm) is shown in Figure 5.

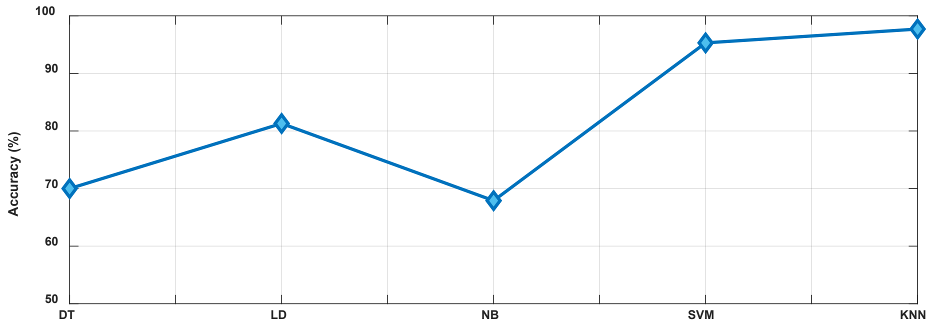

Figure 5. Comparison of accuracy results with other classifiers (DT: Decision Tree, LD: Linear Discriminant, NB: Naïve Bayes, SVM: Support Vector Machine, KNN: K Nearest Neighbor Algorithm)

In the proposed method, the confusion matrix values are calculated by running 100 iterations for the KNN classifier. The confusion matrix results are shown in Figure 6.

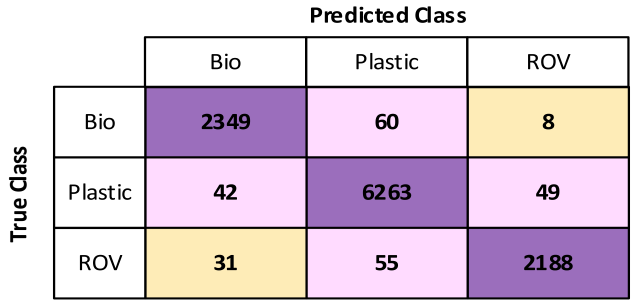

Figure 6. The result of the confusion matrix calculated with 100 iterations of the proposed method

The accuracy, precision, and recall results of the KNN classifier used for 100 iterations are tabulated in Table 4.

Table 4. Performance results of the proposed KNN classifier

	Accuracy (%)	Precision (%)	Recall (%)
Maximum	97.78	97.54	97.34
Minimum	97.56	97.23	97.06
Average	97.67	97.40	97.22
Standard Deviation	0.049	0.062	0.065

The class-based accuracy results of the proposed method are shown in Figure 7.

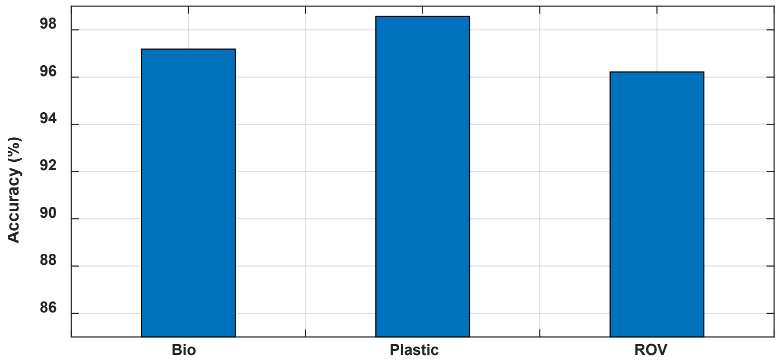

Figure 7. Class-based accuracy results of the proposed method

When the studies are examined, there are very few studies in the literature with a mixed (sea creature and garbage) data set. Moorton et al. [11]tested only sea creatures (sea cucumber, sea urchin, and scallop) considering the dataset. Iron et al. [9] examined only garbage (plastic bottles, glass bottles, and packaging) images in the data set they used. In this section, a comparison is made with our study based on ICRA19-Trash datasets. The proposed method was applied to the ICRA19-Trash dataset and obtained high classification accuracy. To demonstrate our high classification ability, our results were compared with other methods, and the results are listed in Table 5. The results of the existing literature studies can be summarized in Table 5.

Table 5. Summary of comparison with other state-of-the-art methods using the Trash-ICRA19 dataset.

	Dataset	Number of Images	mAP	Accuracy (%)	Precision (%)	Recall(%)	Geometric Mean (%)	F-Score(%)
Fulton et al. [1]	Trash-ICRA19	5720	81.0	-	-	-	-	-
Wu et al. [6]	Trash-ICRA19	7684	97.5	-	-	-	-	-
Our method	Trash-ICRA19	11060	-	97.78	97.54	97.34	97.34	97.44

Fulton et al. [1] used the Trash-ICRA19 dataset, which consists of garbage, sea creatures, and rov objects. They achieved an 81% success rate with the Faster RCNN method of 5720 images. Wu et al. [6] used 7684 images for the Trash-ICRA19 dataset. For suggested methods, see Fulton et al. [1] 81.0% Wu et al. [6] calculated an accuracy of 97.5%. In the literature, the classification success for Trash-ICRA19 datasets has been calculated as over 80%. Our proposed method KNN model has 97.78% higher accuracy.

4. Conclusions

In this study, the KNN algorithm was applied to classify underwater objects, their analyses were made and the results were recorded. In our study, training was carried out using the Trash-ICRA19 dataset, which is a publicly available dataset. Our study has shown good results using classification algorithms. When we compare the accuracy results with other classifiers, it is seen that the KNN classifier gives the best results for this study. Our recommendation calculated 97.78% classification accuracy. These results and comparisons show that it is successful in classifying underwater image types. The classification of our study with high accuracy constitutes the main motivation. The reason why the Trash-ICRA19 dataset is used instead of other datasets in the literature is that the dataset consists of a large dataset consisting of 11060 images. Another reason is that it consists of two classes that are very important for marine ecosystems, namely sea creatures and garbage images. While the size of the data set makes it easier for us to detect and classify objects, the fact that the number of classes is more than one makes our work more difficult. Despite this disadvantage, a high success rate has been achieved with KNN classification. In future studies, it is envisaged to detect real-time garbage and living things using underwater robots. Also, our method can be tested on larger datasets with more classes.

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6. Author Contribution Statement

In the study, Kübra Demir contributed to the creation of the idea, design, and literature review; Orhan Yaman contributed to the analysis of the results, the provision of materials, and the review of the results.

7. Ethics Committee Approval and Conflict of Interest

There is no need for an ethics committee approval in the prepared article. There is no conflict of interest with any person/institution in the prepared article.

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