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A Network based Approach for Automated Identification of Calanoid Copepods using Deep Learning

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ABSTRACT

In recent years, deep learning techniques have played an important role in the biological field. The present study proposes a convolutional neural network approach for identification of calanoid copepods *Temora discaudata* and *Canthocalanus pauper*. *T. discaudata* and *C. pauper* classifies with the image dataset to develop for classifying the species. Nowadays, ecological science is improved by advances in Artificial Intelligence (AI) for the classification of different species images. The digital image technique includes augmentation, pre-processing, segmentation, and classification, and is implemented based on deep learning algorithms to improve classification of species with different features with Convolutional Neural Networks (CNNs). This study proposed pre-processing with the size of 64×64 and 224×224 of the calanoid species, then augmentation followed by classification. Also, image processing is focused to implement the original image to the binary mask for yielding better accuracy. During the classification of the *T. discaudata* and *C. pauper* images, the macro average and weighted average are calculated for finding 90% and 93% accuracy, respectively of the training model. The conventional method of identification of calanoid copepods is tedious, while, the CNN can automatically predict the species features from the data set. Finally, the experiment analyzed the *T. discaudata* and *C. pauper* datasets in the technical aspect of digital image processing techniques in Artificial Intelligence.

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Keywords: Artificial intelligence; Calanoid copepods; Convolutional neural network; Deep learning

1. Introduction

Convolutional Neural Networks (CNNs) can process large datasets with speed and accuracy, which improves identification efficiency over conventional approaches. It can reduce the possibility of human error and inter-observer variability in identifications of calanoid copepods by learning to detect tiny traits and variances that may be challenging for human observers to perceive. CNNs are capable of processing images far more quickly than humans, which might be useful when handling massive amounts of data.

Copepoda is a subclass that belongs to the subphylum Crustacea of the phylum Arthropoda [1]. Copepods are the most numerous metazoans, accounting for over 80% of all zooplankton samples in the entire ocean [2]. They outnumber all other zooplankton communities in terms of abundance and biomass in the marine environment [3]. Copepods are the most studied marine zooplankton group. There are around 540 copepod species in Indian waters, where the Calanoida is the most prevalent group, with the Cyclopoida and Harpacticoida being less common [4]. Calanoid copepods are most common in tropical and subtropical habitats, and their structure and habitat are quite diverse [5]. Numerous cryptic and sister species of copepods are difficult to detect due to their high species diversity and resemblance [3]. The order was taxonomically described several years ago, but subdivision has been problematic due to the wide range of characteristics [6]. The present conventional taxonomic corporation of the Calanoida was constructed [7-9].

The diversified preservation of calanoid copepod shape and structure has led to significant challenges in differentiating the several sister species, many of which are distinguished by minute morphological and morphometrical differences [10]. Copepod taxonomists with expertise in species identification are becoming scarce; as a result, species misidentification may become increasingly common in ecological and oceanographic investigations. As a result, novel ways to species identification are necessary. Plankton samples have been analyzed using morphological characters [11]. Achieving accuracy in the taxonomic classification of calanoid copepods is a significantly complex task, such as the differentiation between morphologically similar taxa [12]. The development of computer technology has enabled artificial intelligence (AI), machine learning (ML), and deep learning (DL). Machine learning and deep learning are the types of AI that use a complex algorithm to learn from the data to improve, describe, and predict the outcomes of the input data [13]. Tang et al. [14] made one of the earliest attempts to automatically classify photos of plankton. They employed gray-scale morphological granulometries and Fourier descriptors with invariant moment characteristics. Their technique produced photographs of plankton with an accuracy of 90% [15]. They used support vector machines in conjunction with active learning to create a system. Tang et al. [14] developed a novel approach based on normalized multilevel dominant eigenvector estimation.

The specialized machine learning technique used convolution operation in a neural network to process any data which has a grid-like topology, such as in time-series data (single dimension) or image data (two dimensions) [16, 17]. Several studies have used deep learning techniques, particularly CNN, to automate plankton image acquisition, identification, and enumeration. Cheng et al. [18] have constructed an enhanced CNN model combined with Support Vector Machine (SVM) to conduct an in-situ automatic zooplankton identification and enumeration. On the other hand, Pedraza et al. [19] have used deep learning and the CNN model to classify 80 species of diatoms from an extensive dataset of 160,000 brightfield image samples.

Several classification methods such as neural network, structural, fuzzy and transform based techniques have been used in biological image identification systems. An Artificial Neural Network (ANN) is a mathematical model composed of many processing units that communicate by interconnected variables [20]. The multilayer structure of ANN enables learning from complex input image features and generates a single output [21]. Freeman and Skapura [22], have shown satisfying results in complex classifications of biological images such as insects [23], microinvertebrates [24], algae [25, 26] fish [27, 28], leaves and butterflies [27], protozoans and metazoans [29], dinoflagellates [30], human helminth eggs [31], and copepods [32]. The present study is emphasizing the uses of CNN, image processing, and a deep learning approach to classify the calanoid copepods. The traits of copepods may be helpful in predicting species in particular habitats or regions where the species are known to exist or where there is little diversity. Ecologists and non-specialists alike can benefit from image capture and processing systems that enable quick and impartial digital copepod identification.

2. Materials and Methods

Copepod routine identification can be extremely difficult and time-consuming, requiring taxonomic knowledge, experience, and a great deal of work. Therefore, it is imperative to implement new techniques and strategies to automatically identify and categorize copepod specimens.

A dataset is used to define the structure and operation of different biological species by using an algorithm to find the predictable whole dataset in Digital Image Processing (DIP) by deep learning techniques. A different image of two calanoid copepod species *T. discaudata* and *C. pauper* is captured and collected as the high-quality data set for sending to the training process. The innovative steps involved in this paper are (i) Image augmentation is then applied to increase the dataset count to achieve much better accuracy by applying different conversions of images like angle shift, rotation, etc. Real-world data generally contains noises, and missing values, and may be in an unusable format that cannot be directly used for deep learning models. (ii) Data preprocessing is a required task for cleaning the data and making it suitable for a deep learning model which also increases the accuracy and efficiency of a deep learning model.

Fig. 1 shows the steps of innovation applied in the DIP techniques to produce the output image of *C. pauper* and *T. discaudata*. It is the proposed system to deliver the different image information for the analysis of augmentation, pre-processing, segmentation and classification by using the CNN model based on the AI.

2.1 Image augmentation

Augmentation will perform for better contrast to the sample training set by randomly altering the image contrast. Image augmentation is deployed to the training input data set of different species, classes, and class types in the water. There is a difference between both image pre-processing and image augmentation for categories of the organism i.e., pre-processing is managed to training and training set, but the image augmentation is processed for only the training data to increase better accuracy and brighter.

Summary of Recent Methods of Plankton identification

Author(s)	Year	Description of study	Reference
Kraft et al.,	2022	Towards operational phytoplankton recognition with automated high-throughput imaging near-real-time data processing, and convolutional neural	https://doi.org/10.3389/fmars.2022.867695
Kyathanahally et al.,	2021	Deep learning classification of lake zooplankton	https:// doi.org/10.3389/fmicb.2021.746297
Li et al,,	2021	Plankton detection with adversarial learning and a densely connected deep learning model for class Imbalanced Distribution	https:// doi.org/10.3390/jmse9060636
Prakasa et al.,	2021	Development of segmentation algorithm for determining planktonic objects from microscopic images	https://doi.org/10.1088/1755-1315/944/1/ 012025
Toit	2021	Enhanced Deep Learning Feature Extraction for Plankton Taxonomy	https: //doi.org/10.1145/3487923.3487930
Cheng et al.,	2019	Enhanced convolutional neural network for plankton identification and enumeration	https://doi.org/10.1371/journal.pone.0219570
Luo et al.,	2018	Automated plankton image analysis using convolutional neural networks	https://doi.org/10.1002/lom3.10285
Leow et al.,	2015	Automated identification of copepods using digital image processing and artificial neural network	https: //doi.org/10.1186/1471-2105-16-S18-S4
Yu et al.,	2013	Automated identification of animal species in camera trap images	https: //doi.org/10.1186/1687-5281-2013-52

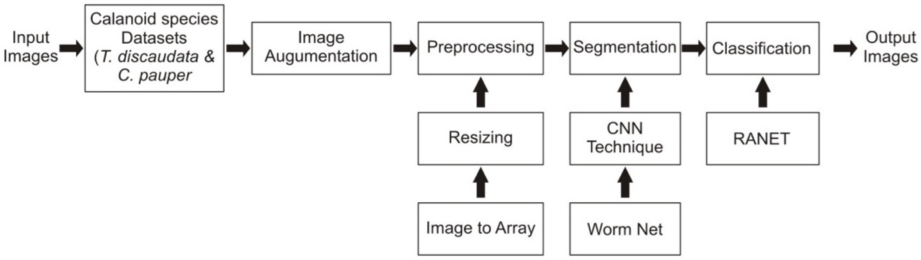

Fig. 1. Block Diagram of image processing technique for calanoid copepod.

2.2 Pre-processing

The pre-processing steps are involved in the DIP to format images before doing the different training models. Mostly, it is used to perform resizing, awareness, and for implementation of the various colors for the images. The pre-processing is required to clean the image data by connecting with the deep learning techniques such as Convolutional Neural Networks (CNN) are operated for all the images to be similar in size in the Numpy arrays. It helps to reduce the time for training and increase the speed for better performance in the image data.

The basic operation of the pre-processing is brightness correction, geometric transformations, image filtering, and applying the Fourier transform with image restoration. These steps are used to bring the brightness, suppress the attenuation, and for bringing many features of pixels in gray values to color images.

2.3 Segmentation

Segmentation mainly helps to support dividing an image into many parts or many regions according to the pixels in the input image. It makes the image simpler by breaking it into sub-images and also decreases the complexity of an entire image. It determines the various labels for each pixel to segment, which belongs to the same category for the entire region. The important advantages are reducing the inference time duration. The segmentation used the deep learning technique of Convolutional Neural Networks (CNN) to initiate with various sublayers. The CNN is analyzed by the worm net algorithms to divide the number of pixels, in the CNN-based worm detection module, we propose three kinds of data preprocessing methods: frequency processing, frequency weighted processing, and difference processing, and use CNN to train the model for worm detection from color to black and white for the sizes 128 × 128 × 3. The two-dimensional max pooling is enhanced to do the activation and prediction in the worm net algorithm.

Thus, the Python implementation is taken by pool1 = MaxPooling2D (pool_size = (2, 2)) (conv1) for delivering the images into many sub-images. The deep learning technique is focused on the max pooling 2D to convolution the sub layer to normalize the inputs in the dropout and determine better accuracy. The bidirectional convolution layer is used to implement the segmentation in the black-and-white color of the original images. The dropout defines the sub layers, size, and dimension of the original image, which is developed on the deep learning in the CNN layers as follows: drop3 = Dropout (0.5)(conv3)pool3 = MaxPooling2D(pool size = (2, 2)) (conv3).

For a feature map having dimensions $nh \times nw \times nc$, the dimensions of output obtained after a pooling layer are

$$(nh - f + 1)/s \times (nw - f + 1)/s \times nc,$$

where nh is height of feature map, nw is width of feature map, nc is number of channels in the feature map, f is size of filter, and s is stride length.

2.4 Classification

Image classification is the process of classifying the species' image into the same type or same class group of images based on visual perception. Image classification algorithms can figure out the group of images very clearly. In this paper, the two organisms such as *T. discaudata* and *C. pauper* are applied to classify for extracting information from images. It is well known that supervised classification can analyze the interaction between the pixels in the image. A supervised classification process is applied in the two species as the training data set in the form of homogenesis. Each training set must focus on 20 to 25 pixels in the group of classes.

Fig. 2 gives the flow chart of the proposed system. Firstly, the image dataset must be collected in JPG. Secondly, the dataset is processed to the augmentation which provides the high color contrast passed to the pre-processing techniques. Thirdly segmentation resizes the pixel and converts the pixels to black and white through masking by one. Finally, the image is classified as the two species as *T. discaudata* and *C. pauper* with the parameter by generating the image-trained model.

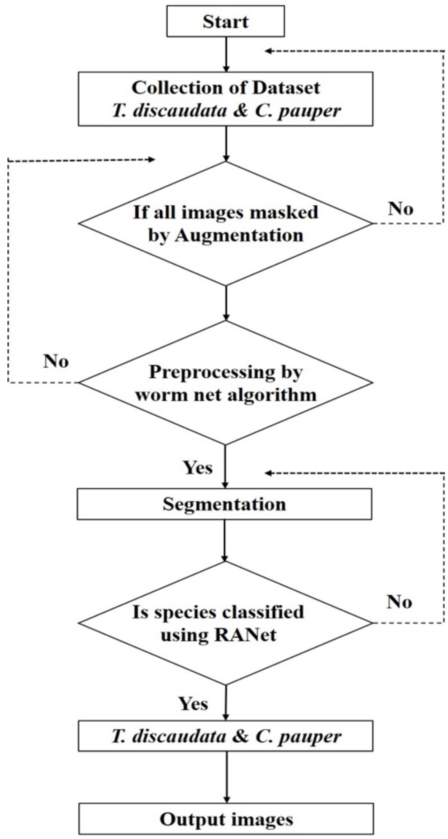

Fig. 2. Flow Chart of Image Processing based on CNN Model.

There are two types of data preprocessing, resizing images - Rescaling and cropping to resize image data to match the input size of a network. (iii) Image to Array conversion - Images are converted into Numpy array in Height, Width, and Channel format. (iv) Image annotation is the process of labeling or classifying an image using text, annotation tools, or both. Many annotations are used in which segmentation is applied for this project. (v) Segmentation is used to recognize and understand what's in the image at the pixel level. After this, the model is trained for segmentation using the newly developed WormNet segmentation algorithm and (vi) the classification is trained using the RANet classification algorithm. After the training is over, the model files are generated with which the prediction and segmentation are performed. Thus, this project provides an efficient way to segment the presence of insects and also give an accurate prediction. In this paper, the calanoid datasets are collected to be divided into two processes such as training and testing for *T. discaudata* and *C. pauper* as shown in Fig. 3

2.5 Convolutional Neural Networks (CNN)

A CNN model is one of the thrust areas of neural networks, which excels on many of the DIP techniques such as identifying counterfeit (IC), IS, Video Processing, Speech Recognition, etc. CNN is divided into many layers such as convolutional layers, subsampling layers, and nonlinear layers to separate the features without affecting the data images. In this work, calanoid copepod species are examined for the extraction of their different images by using the Ranet in CNN models on the digital image processing to be attached spatially with their characteristics. Mostly, the RAN plays a vital role to provide feed-forward on the object-aware characteristic of the neural networks. CNN always depends on the capacity of each pixel to infer the dense features with better characters to remove many noisy pictures. RAN helps to recognize in groups, avoid complicated and efficient in classifying the pixel of images.

To identify the species of calanoid copepods family automatically, the deep learning techniques work with the CNN to analyze the image visually in the matrix on neural networks. The CNN models consist of several layers but will calculate mathematically the average weight of several inputs and outputs in the pixel values of an image. Then it starts to evolve on each edge of the next layers to extract the image features such as objects, faces, and points as the output. Mostly, the convolutional layers are used to classify the layer to get the binary values of 0 and 1's to define the images in the input of the final layer. The final layer finds the objects of the species whether it is a *T. discaudata* or *C. pauper* of the calanoid copepods. Fig. 4 shows the structure of the CNN model and how the input images of calanoid species are segmented to determine the output.

Fig. 3. Sample data set of *T. discaudata* and *C. pauper.*

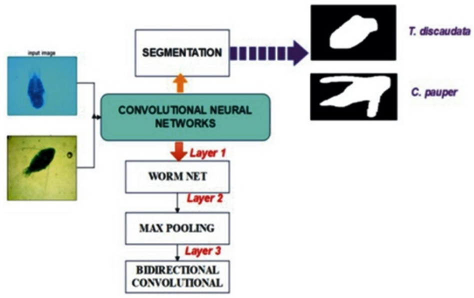

Fig. 4. Identification of calanoid copepods to segment by CNN model.

The following steps are involved in the CNN model for identification of copepods in DIP techniques. Initially, the calanoid species dataset is loaded to train and test for digit recognition. The steps required for the prediction of species in the Convolutional Neural Network are given below.

STEP 1: Import the colonoid copepods dataset in library.
STEP 2: Assign the size and pixels of each image.
STEP 3: Normalize the data from (0-255) to (0-1) to identify the image.
STEP 4: Determine the model function as ReLu.
STEP 5: Execute the CNN model with the above three layers.
STEP 6: Calculate the accuracy and error percentage for the *T. discaudata* or *C. pauper.*

3. Results and Discussion

The digital image processing techniques are implicated in the analysis of the experimental results in the CNN model on deep learning. Culverhouse et al. [12]; Hu and Davis [33] have trained a dataset for obtaining 67-83% and they suggest a 90% benchmark in human classification. Here proposed DIP on DL to achieve the 96% of better performance of image classification. Nowadays, the community of the calanoid copepods is very sharp to classify very exactly as per the environmental conditions. Cowen et al. [34] have predicted the threshold as less than 1% for 31-36 classes by using machine learning, and 90% is evolved to gain precision in many of the biological sciences. Faillettaz et al. [35] recognize the better images to maintain in finding the classifier of the copepods and they involve in the layer of the CNN model for the Sparse ConvNet layer. CNN is always playing a vital role in ML methods to extract image features [34]. Moreover, Fernandes et al. [37] determine the training set to be classified in the network system by using the Naïve Bayes classifier.

These proposed CNN models on DIP techniques demonstrate and illustrate the analytical results for various steps such as (1) Image Augmentation (2) Image Pre-processing (3) Image Segmentation and (4) Classification with the proposed algorithm CNN model in AI from the Figs. 5-10.

3.1 Image Augmentation (IA)

IA is a technique to expand the size of a training set to convert the image pixels from the existing method. It works out from overfitting the image to recover for better performance. The *C. pauper* and *T. discaudata* datasets are enhanced by augmenting the different types of data efficiently and easily from the original image.

Fig. 5a gives the input image for augmentation as *T. discaudata* species; it is augmented as rotation in a different direction with various sizes and the species with reduced size. Hence Fig. 5b shows the images are to be analyzed for the augmentation in various directions in high contrast with better accuracy.

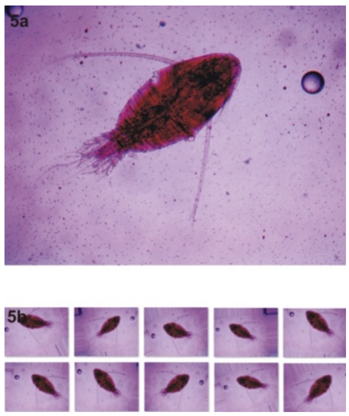

Fig. 5. a) Input image for augmentation; b) Output of augmentation.

3.2 Image Pre-processing (IP)

The number of datasets of *C. pauper* and *T. discaudata* has been selected in the seashore for doing an analytical experiment by using digital image processing as shown in Fig. 3. The sample data set was captured by the digital camera with low contrast in some situation. Hence the pre-processing helps to improve the model to increase high contrast with different colors as shown in Fig. 6. Here, the two species are about to be pre-processed in different structures with resizing for 224×224 and 64×64 as shown in Figs. 6-8. The image processing will augment the input images to manipulate in a different version to value the quality, increasing the size and increasing the pixels by adding extra to it.

The *C. pauper* image is given in the pre-processing in random size; once the testing is completed, the size of 224×224 pre-processed output image is obtained. Figs. 6 a and b show the input random size and output pre-processed image of the *C. pauper*.

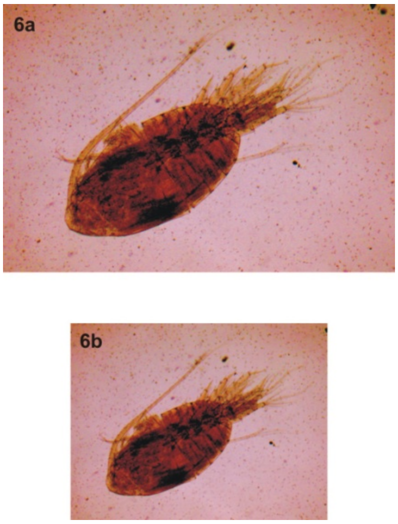

Fig. 6. Simple Image Pre-processing by 224×224; a) Input random size; b) Output 224×224 pre-processed.

In Fig. 7, the input image in random size is applied for pre-processing to reduce the size and high contrast of the image. Then it carries the output from image pixels into the Numpy array models for training. Fig. 8 shows the aspect image pre-processing and it is converted into the output image with the size of 64×64 to be pre-processed.

After pre-processing is done with two different sizes 224 and 64 in the algorithm, and the binary image is converted to an array with an algorithm, the binary masking and resizing must be involved to find the accuracy, macro average, and weighted average.

Fig. 7. Image to array pre-processing size; a) Input random size; b) Convert the image pixels in NumPy array.

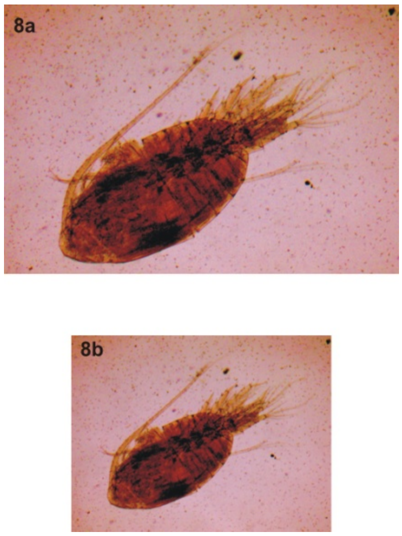

Fig. 8. Aspect image pre-processing by 64×64 size; a) Input random size; b) Output 64×64 pre-processed.

3.3 Create binary masks for *T. discaudata* and *C. pauper*

Binary Masking is one of the Image Processing (IP) techniques which is used to isolate and modify some part of a species. It is discovered by thresholding i.e., converting the image species from black to white image as given in Fig. 9. Then the binary masking image is modified to the original image using the powerful Python tool. This mask image is analyzed ranging from zero percent to 100 percent for improving the pixel intensity values. This paper utilizes 35 masks by smoothing the images and resizes with modernization. During masking, the threshold has taken 150, reshaping the mask as zeros and updating the colors and order with all pixels in the grayscale images will be represented as "plt.Scattershape1_x, shape1_y, zorder = 2, color = 'red', marker = '.', s = 55". The pixel coordinates x and y are initialized with zero order for shapes 1 and 2 with red color insisted with size 55.

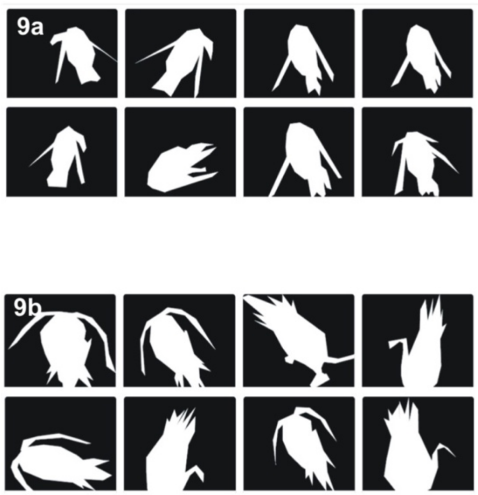

Fig. 9. a) Binary masks output of *C. pauper*; b) Binary masks output of *T. discaudata.*

3.4 Image Segmentation (IS)

Figs. 10(a)-(d) shows the segmentation of *T. discaudata* and *C. pauper* with a different structure based on the various color changes to the segmented images in white color, as the values are considered to be 1. The training dataset is taken to compile through the Model.fit, val_loss for validation loss, and Epoch for how many iterations are implemented. Once the segmentation process is completed, the results are yielded as epoch increases to reduce the loss available in the original image.

Reducing the loss automatically increases the accuracy of the segmented image in the image processing as given in Fig. 10. Thus, the trained model fit has established the values for both the *T. discaudata* and *C. pauper* with different parameters such as precision, recall, f1-score, support accuracy, macro average, and weighted average.

3.5 Image Classification (IC)

To classify the species, the Ranet is used to determine the accuracy and average of various sizes of an image with the prediction of an original image. In Fig. 10, the structure of the image must be monitored to analyze the average weight and size of the classified image in the range of the x-axis and y-axis. Image classification detects the classes of species that compares with the same pattern without modifying the image information.

The generation of the trained model is compiled to improve the accuracy of the image in an image as given in Fig. 11. After classification using the Ranet, the step of the algorithm used in the Python program is given as class names = ['Canthocalanus pauper', '*Temora discaudata*'] and Print ('Classification:', classNames[preds[0]]). Finally, the segmented image is classified by using the supervised classification process through the Ranet as shown in Figs. 10(a)-(b).

Thus, the set of the training model and parameters of *C. pauper* and *T. discaudata* are obtained by using the algorithm of Ranet in the Python tool. In Table 1, the accuracy is yielded as 93% and 90% for the dataset of *C. pauper* and *T. discaudata*. Moreover, the average of the macro in the image dataset is determined as 0.98 and 0.97, and the average weight for both is 0.97. In Table 2, the parameter of precision, recall, F1-score, and support are determined to measure the feature extraction of the prediction of the images in the classification process.

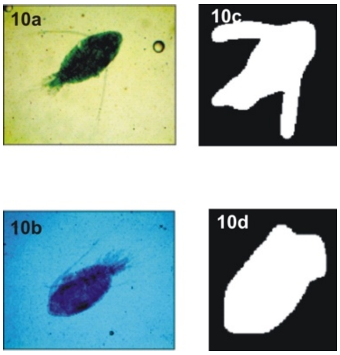

Fig. 10. Image segmentation of *T. discaudata* (a and c) and *C. pauper* (b and d).

Table 1. Classification of two species (*T. discaudata* and *C. pauper*).

S. No.	Parameters	*T. discaudata*	*C. pauper*
1	Accuracy	90%	93%
2	Macro Average	0.97	0.98
3	Weighted Average	0.97	0.97

Table 2. Generation of parameter trained model.

S. No.	Parameters	*T. discaudata*	*C. pauper*
1	Precision	1.00	0.96
2	Recall	0.93	1.00
3	F!-Score	0.97	0.98
4	Support	15	23

4. Conclusion

The study of this paper is implemented by CNNs is extremely analyze the experimental aspect, which is presented by using Python software. In general, copepod identification, particularly calanoid copeods *C. pauper* and *T. discaudata,* is a laborious process. Thus, the proposed system is analyzed to produce the dataset from the original image to an augmented, pre-processed image on 64×64 and 224×224 with the image-to-array process. Then the segmentation is yielded by binary masking, and resizing, after the max-pooling 2D is insisted to use the CNN algorithm on deep learning techniques.

Once the image is classified, the parameter training dataset of the proposed system in Tables 1-2 is determined with better performance. The parameter of *C. pauper* is accuracy (93%), macro average (0.98), weighted average (0.97) and *T. discaudata* are accuracy (90%), macro average (0.97), and weighted average (0.97) as illustrated in the classification report. The generation of the training dataset model is qualified for precision (0.96), recall (1), F1-score (0.98), and support (23) in *C. pauper*. In *T. discaudata*, the precision (1), recall (0.93), F1-score (0.97), and support (15) are obtained in the experimental output. Hence the approach of the prediction of the two species in the feature extraction is highly effective. The CNN model works through the Python software tool to indicate the results of better accuracy and the proposed ensemble provides the outage performance achieved with the researched techniques in image processing.

Algorithms are necessary for the effective processing and classification of massive volumes of plankton data. An extensive comparison of CNN's performance findings between two plankton sets is presented in this paper. The results indicate an improvement in categorization accuracy. The CNN's capacity to scale for the classification of additional classes without requiring feature design is one of its main advantages. We intend to expand on this research in the future by comparing our findings with those of hybrid convolutional neural networks.

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