ISBN- 978-989-9121-05-8
42nd MADRID International Conference on "Advances in Science & Technology"
(MICAST-2022)
Madrid (Spain)June 22-24, 2022

Detection of Biomass in Lake Areas using Artificial Intelligence: Applying a Study Case-Brates Lake, Galati, Romania

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***Abstract*:** *Biomass continues to be the main source of renewable energy in the EU, accounting for almost 60%, with the largest end-user of biomass being the heating and cooling sector, which uses about 75% of all biomasses. The cartographic activity of the area of the lake areas supposes the elaboration of the maps, of the topographic plans and the identification of the surfaces that represent biomass sources. At the same time, it is necessary to inventory the vegetation present in the mapped areas, to follow the productivity cycle of the crops that will be used as biomass, to identify possible disturbing factors of crops (temperature, humidity, existence of pollution sources, etc.). To detect biomass, we can use convolutional neural networks (CNN), coupled with a special type of feedforward neural networks that consist of several convolution layers and grouping layers. A feedforward neural network is an artificial neural network in which connections between nodes do not form a loop. These networks, which perform patterns like the activity of neurons in the brain, are generally presented as systems of interconnected processing units (artificial neurons) that can calculate values from inputs, resulting in an output that can be used in later units. Artificial neurons are basically processing units that compute some operations on several input variables and usually have an output calculated by the activation function. For this research, an experimental design using artificial intelligence was made to valorize it energetically.*

Keywords: *biomass, artificial intelligence, lake areas*

1. Introduction

Artificial intelligence, and more precisely, neural networks, can be used to determine the presence of biomass in lake areas from satellite images or obtained with the help of a drone, by recognizing the surfaces where reeds or rushes are present. Recent years have seen deep learning become a viable solution for image recognition and classification, based on the fact that it no longer requires manual feature extraction. [1]

Deep learning is a machine learning technique that makes use of algorithms modeled after the function and structure of the human brain. This represents the artificial neural networks. Deep learning represents the simultaneous learning of both features and classifiers and makes use of training data to classify the content of the image without specifying the characteristics of the image beforehand. Of all deep learning networks, the most popular one is the Convolutional Neural Network (CNN). It is used for learning visual features in different image processing and remote sensing applications. [1-5]

In recent years, the research showed that the convolutional neural network is effective for a variety of applications. Because of this, CNN method is used extensively to accomplish many tasks in different academic and industrial fields. This includes plant science. Furthermore, research pointed out that CNN can accurately detect different plant diseases and it can classify plant species in an herbarium [4].

Fig. 1: Examples of images of the studied lake areas

CNN represents an encouraging technology in the remote sensing study field. In the past years, CNNs have begun to be used for tagging scenes and detecting objects in images. Most of the previous research has used a

supervised learning technique and has shown that CNNs can precisely detect objects in images. Unfortunately, the studies using convolutional neural network to detect vegetation in images is limited [6-8].

Studies have been conducted that have successfully detected high-precision palm trees using this technology. CNNs have also been used to detect wild shrubs in satellite imagery, providing better results than conventional methods of detecting objects [9-12].

2. Materials and methods

In his paper it was selected the Brates Lake area, found in Galati County, Romania. The images used were acquired with the help of a professional UAV.

The Matlab software package was used to perform the convolutional neural network and the image preprocessing step. This software is a numerical computing and statistical analysis development environment that contains the multi-paradigm programming language and a numerical computing environment developed by MathWorks. Matlab allows the manipulation of matrices, the graphical representation of functions and data, the implementation of algorithms, user interface design and the interfacing with programs developed in a variety of other languages. Although Matlab is primarily intended for numerical computing, a number of optional tools use the MuPAD symbolic engine that allows symbolic computing to be used. An optional package, Simulink, supports multiple domains graphics computer simulations and a model-based approach to design options for systems that are embedded and dynamic.

3. Image preprocessing

Before they can be used by the neural network, the images go through the preprocessing stage. This stage is a set of techniques that aim to improve complex images in terms of visual appearance, reduce noise and artifacts generated by acquisition tools, manipulate brightness, and contrast or accentuate the edges. Preprocessing is an important step because proper enhancement leads to either a comprehensive analysis of the image's texture or a correct segmentation of objects of interest in an image. Image enhancement uses linear and nonlinear filtering methods or wavelets and Fourier transforms [13].

CLAHE (Contrast-limited adaptive histogram equalization) represents the operation of leveling the histogram by adaptive filtering with contrast limitation and is based on a generalization of the cases of uniformity of normal and adaptive histograms, being used for local improvement of contrast in images. This technique works on small contextual regions, where the uniformity of the histogram and the local improvement of the contrast are achieved. Subsequently, these small neighboring regions are joined using a bilinear interpolation method to avoid amplifying any unwanted information. The linear contrast amplification factor and the number of intervals used in changing the histogram are limited (by using a chosen threshold) so that the redistributed histogram does not exceed the set limit [14,15].

The Gaussian filter describes a class of linear smoothing filters, according to the shape of the Gaussian function. The Gaussian operator is a two-dimensional smoothing operator used to blur images, eliminate noise and detail. The Gaussian filter enjoys optimization properties, being used successfully in various image processing applications, in applications specific to the field of engineering and computer vision [16,17].

4. Convolutional neural networks method

To detect biomass, we can use CNNs, coupled with a particular type of feedforward neural networks composed of several convolution layers and grouping layers [1,6].

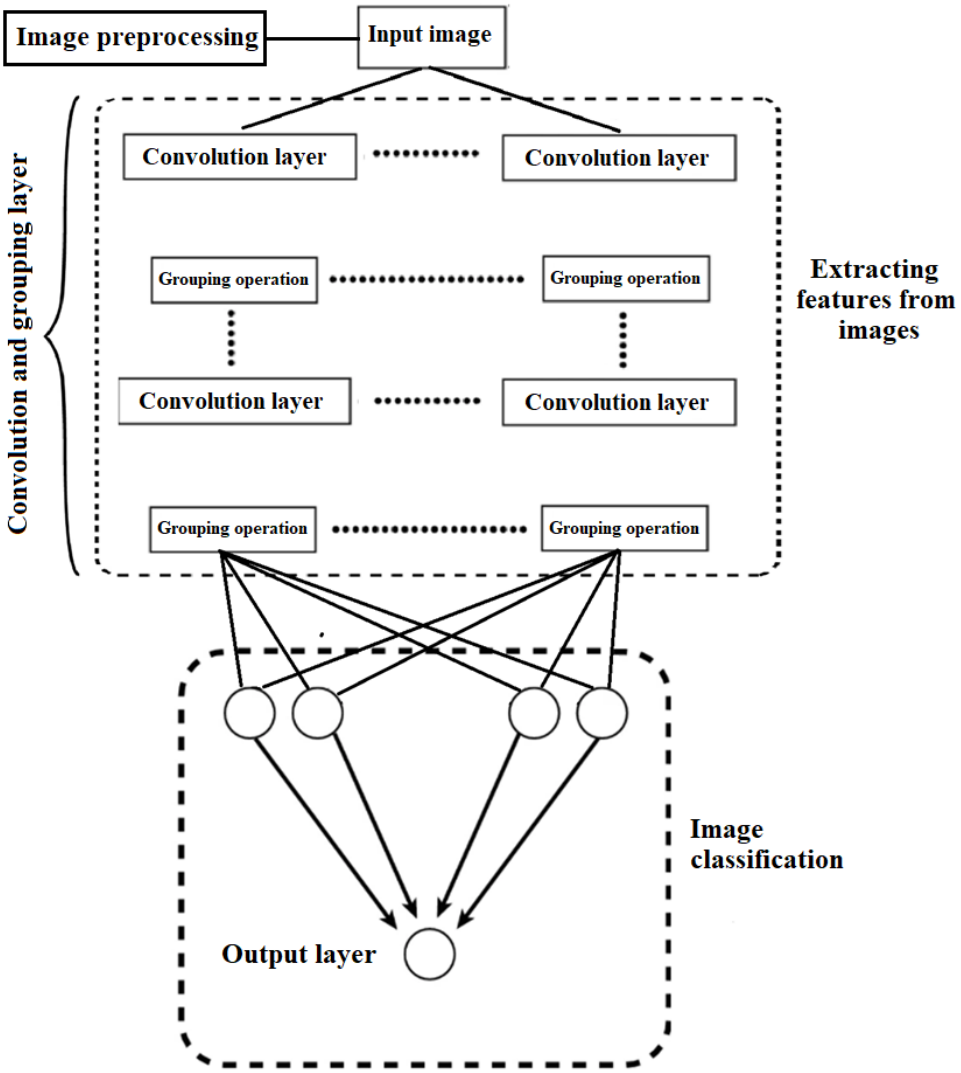

Fig. 2: Outline of convolutional neural networks

A feedforward neural network represents an artificial network in which connections between nodes do not make a loop. These networks, which perform models similar to the activity of neurons found in the human brain, are generally used as systems of interconnected artificial neurons that are calculating values from input values, generating in an output that can be used in later units. Artificial neurons can be defined as processing units that calculate some operations on several input variables and usually have an output calculated by the activation function[1-3].

A convolutional neural network consists of a convolution layer and a grouping layer. The convolution layer is responsible in capturing features in images. During this process, a fixed-size filter passes over images and extracts color patterns from images. After each convolution layer, there are grouping layers that must reduce the variance of the features; this is done by calculating operations of a certain feature on a region of interest of an image.

The grouping layer has two features. The first one is to minimize the feature's position sensitivity drawn at the convolution layer, so the output information of the grouping layer does not change. In addition to that, it plays the function of enhancing the recipient area for the next convolution layer. Two operations can be performed on the grouping layers, namely maximum and average operations [1,6, 18]. This process assures that the identical outcomes can be captured even in the case when the characteristic of the image presents small rotations or translations, and this is crucial for the classification and detection of objects. Thus, the grouping

layer is responsible for the sampling operation of the output of the convolution layer and keeping the spatial position of the image, and also to select the utmost important attributes for the following layers. Furthermore, a certain number of convolution and grouping layers, there are layers which are fully connected, and take all the neurons from the prior layer and connect them to each neuron in its layer [9].

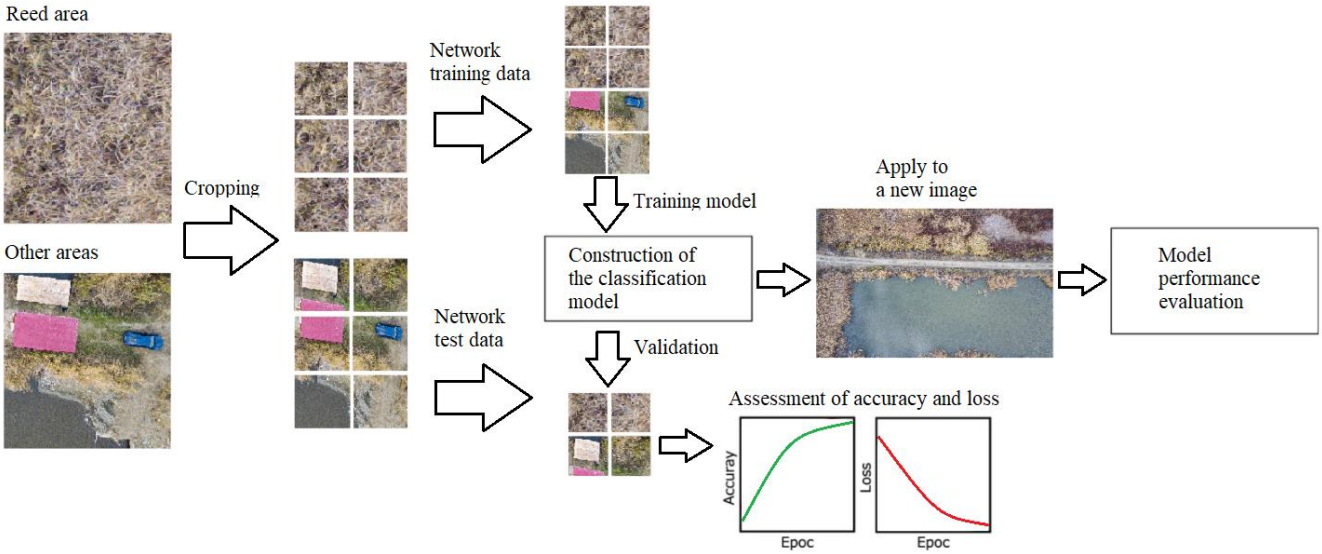

Fig. 3: Scheme of the adopted approach. This image was acquired using a drone

A diagram of the proposed approach is shown in the above figure. The training data of the network are prepared using an image cropping method. First of all, in this method, images are collected in which the reed is 100% present and images not covered with reed. After that, these images are truncated into small squares, with an overlap of 50% both vertically and horizontally. Finally, I used the cropped images as training images [9].

We created a model for classifying images using CNN to detect reed areas. Unlike conventional approaches to forming classifiers with hand-drawn feature extraction, CNN learns the hierarchy of features starting with pixels al the way to classifiers and trains common layers. The last layer of the CNN model is used to detect the reed coverage of images captured by a drone [6,9].

First, all images are randomly shuffled to avoid overlapping training and validation data, followed by the use of 70% of the used images as training information and the other 30% as validation data. The proposed model uses small images as training data and validation data. The network is built with two convolution layers, two grouping layers and one completely connected layer. The model uses a number of 30 training epochs.

This method was validated during each learning era using two functions, accuracy and loss. "Accuracy" represents the precision of the method in classifying validation images, while "loss" is the inaccuracy of the model's prediction. If the model learning is successful, the loss is low, and the accuracy is high.

The confusion matrix is utilised to evaluate the performance of the proposed model. The results of the classification can be divided into the following groups: false positive (FP), true positive (TP), true negative (TN) and false negative (FN).

5. Conclusions

Artificial intelligence algorithms are able to detect reed covered areas from UAV acquired images, with a very high level of accurately. Furthermore, the convolutional neural network method combined with the cropped image techniques represent a powerful tool for high-precision image-based biomass detection in lake areas. Also, there is a huge opportunity to decrease the workload and resources required for biomass detection and mapping as well as enhancing the existing framework of reed monitoring.

6. Acknowledgements

This work was supported by the project "Development of innovative technologies using artificial intelligence to capitalize on biomass in lake areas in order to sustain green energy, financed by the Romanian Ministry of Research and Innovation- Developmental Research Plan Sectorial, Contract no. 1PS/2021.

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