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MAPPING AGRICULTURAL WASTE FOR BIOGAS PRODUCTION USING A FULLY CONVOLUTIONAL NEURAL NETWORK AND REMOTE SENSING IMAGERY

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Abstract. *The increasing generation of waste and depletion of natural resources has led to a growing need for innovative approaches for utilizing different types of waste as potential energy and material resources. Agricultural activities produce large amounts of Agricultural Waste (AW), which, if not adequately managed, can lead to environmental degradation. One potential solution for the effective utilization of AW is converting it into biogas. However, commercializing this process requires a comprehensive understanding of the types and quantities of AW generated. In this paper, the use of a Fully Convolutional Neural Network (FCN), which has rapidly advanced with the progress of Artificial Intelligence and become essential for tasks such as Semantic Segmentation, Object Detection, and Image Classification, is proposed to improve the prediction of AW for biogas production. Furthermore, this paper presents a Deep Learning-based image segmentation method to recognize vineyard fields, which are a significant source of AW, using remote satellite images. The proposed approach can significantly improve the identification of AW sources, and thus contribute to the efficient and sustainable utilization of AW for biogas production.*

Key words: *semantic segmentation, agricultural waste, remote sensing, biogas production, convolutional neural network*

1. INTRODUCTION

Agricultural activities are a significant contributor to the generation of large amounts of organic waste, commonly known as agricultural waste (AW), which requires proper management and disposal to avoid harmful consequences for the environment [1]. Inadequate

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treatment of AW can lead to land, water, and air pollution, as well as fires, which can have severe consequences.

However, AW can also be utilized as a substitute source in various fields of study and business to produce a wide range of goods, including biogas, biofuel, mushrooms, and tempeh as raw materials [2]. The use of agro-industrial waste as a raw material can reduce manufacturing costs and the impact on the environment, thus promoting a sustainable approach.

Over the last few decades, considerable efforts have been made to find new ways of using different types of waste as a resource, considering the trend of increasing waste and decreasing resources. Currently, the most common methods for utilizing AW are composting, biogas production, and burning, depending on the physical and chemical characteristics of the waste.

Various studies have shown that deep learning methods, particularly artificial neural networks (ANNs), have been successfully employed to predict biogas production from agricultural waste. ANNs have been widely used in developing prediction models for biogas production due to their ability to handle complex relationships between inputs and outputs.

In [3] an ANN model with two hidden layers was constructed to simulate the anaerobic digestion operation, as well as to predict the methane production. Jaroenpoj et al. [4] used an ANN to previse methane production from co-digestion of leachate with pineapple peel, while Palaniswamy et al. [5] used an ANN to model and optimize biogas production using mixed substrates of food waste with cow dung. Kana et al. [6] developed an ANN model coupled with a Genetic algorithm to predict the performance of anaerobic digestion from mixed substrates of sawdust, cow dung, banana stem, rice bran and paper waste. Diababa et al. [7] developed a coupled artificial neural network-differential evolution (ANN-DE) for the assessment of the anaerobic digestion of vinasse as a source to produce biogas. In [8] an artificial neural network was constructed to predict the percentage of methane from landfill gases while in [9] an ANN combined with a generic algorithm was trained to give the optimal condition for the conversion of shea butter oil to biodiesel.

Holubar et al. presented in [10] several feed-forward neural networks which were trained to model, and afterward control, methane production in anaerobic digesters. A hierarchical system of nets was developed and embedded in a decision support system to find out which is the best feeding profile. Akbas et al. [11] presented an integrated prediction model based on the neural network with particle swarm optimization to increase the biogas production and biogas quality, contributing on that way to electricity production at the wastewater treatment facility.

In [12], an ANN-based approach is proposed for modeling the biosorption process in the rotating packed bed using different agricultural waste bio sorbents. The paper [13] applies ANN and ANFIS to model and analyze the adsorption of various agricultural wastes, demonstrating high prediction accuracy for Ni2+ removal. Recent advancements in computing hardware have facilitated the development of deep neural networks (DNNs), particularly Convolutional Neural Networks (CNNs) [14], which excel in image-driven pattern recognition tasks. In the realm of waste management, deep learning techniques are employed for waste type detection and classification. Specifically, in [15] the dPEN framework is introduced, a deep learning model that leverages WorldView-3 satellite imagery to accurately map heterogeneous agricultural landscapes by incorporating a progressively expanding network architecture and multi-scale feature learning. Moreover, [16] utilizes CNNs for fast evaluation of compost maturity, achieving excellent results in predicting maturity during the composting process. When faced with limited data on available quantities of certain waste types, such as in biogas production planning, reliable data acquisition methods are sought after. To address this, [17] proposes the fusion of machine vision technology and AlexNet-CNNs for the rapid and accurate detection of postharvest apple pesticide residues, enabling cost-effective residue detection in apples.

In this research, the performance of the Fully Convolutional Network (FCN) for segmentation of the dataset with the aim to recognize the vineyard as a source of AW has been analyzed. Our approach draws on recent successes of deep nets for image segmentation and transfer learning [18]. Multiclass semantic segmentation was performed due to the landform characteristics of the study area. Five-pixel classes were defined as follows: 1) vineyard, 2) cultivated field, 3) forest, 4) road, and 5) others (storage places, etc.).

The experimental setup encompassing the data employed and the VGG-16 network architecture is described in Section 2, while Section 3 reveals the outcomes of the semantic segmentation model and deals with a comprehensive exploration of the performance metrics. Finally, the concluding Section 4 summarizes the findings, while also proposing potential directions for further research.

2. Experimental Setup

2.1. Data

The dataset utilized in this study was obtained from the foothills of Fruška Gora mountain in Serbia. The satellite imagery was acquired from the publicly available database of the Republic Geodetic Bureau and captured at a scale of 1:625. Once the images were acquired some pre-processing steps were performed. Labeling geographic information in satellite remote sensing images is a very complicated and time-consuming task, and labor costs are prohibitively high, making large datasets difficult to produce. So, the original satellite images are cut into small images by performing random window sampling with a window size of 300 × 300 pixels creating the uniform size of the experimental dataset. Images in the dataset are in the RGB color model so, it contains values of the pixels between (0-255) in three different channels.

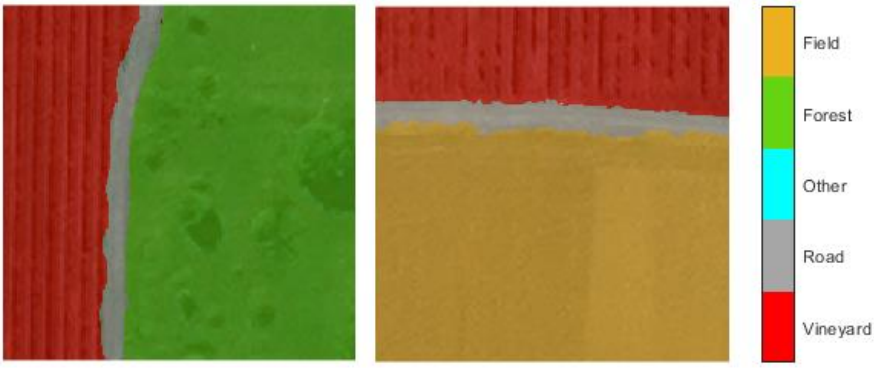

Fig. 1 Ground Truth images

To label images for semantic segmentation, we used MATLAB's application Image Labeler to generate the ground truth annotation for 285 images. This labeling step was crucial for training and evaluating the performance of the semantic segmentation model. Based on the landform characteristics of the research location and the goal of this study, five pixel classes were defined as shown in Figure 1.

The dataset used in this study includes a significant proportion of pixels labeled as vineyard 61%, followed by forest 28.69%, road 4.65%, field 5.58%, and other classes such as storage places and vehicles 0.07% (Figure 2). To address the class imbalance and improve training, class weighting was applied during the model's fine-tuning. The weights used for each class were 0.58, 4.99, 0.87, 1.0, and 40.25, respectively, in the order previously described.

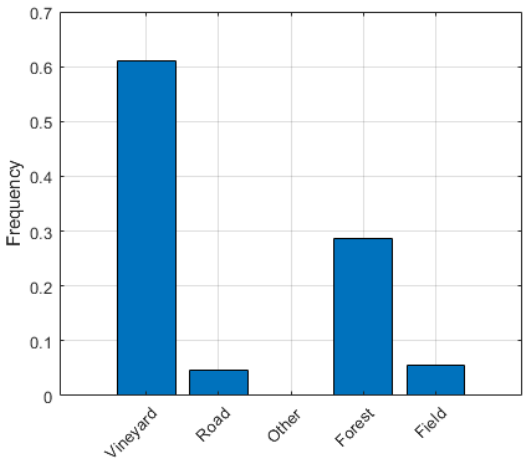

Fig. 2 Distribution of pixels among the different classes in the full dataset

In the context of class imbalance and the pursuit of accurate semantic segmentation, the use of weights in the loss function is imperative. These weights serve to adjust the learning process based on the assigned importance of each class. In this way, the model will not predict the more common classes more frequently just because they are more common. To further improve the segmentation accuracy, a larger dataset can be used. With an expanded dataset, underrepresented classes can be better represented, allowing the model to learn their distinctive features effectively and improve its segmentation performance.

2.2 VGG-16 network

The FCN has been widely recognized for its numerous advantages in the context of image segmentation tasks. It has the ability to preserve spatial information during the segmentation process, ensuring that fine-grained details and boundaries in the segmented regions are accurately captured. This capability allows for a more precise delineation of objects and regions of interest in the images, which is crucial for recognizing the vineyard as a source of AW.

Unlike traditional CNNs that downsample the input image, FCN employs transposed convolutions or upsampling layers to restore the spatial resolution of the output segmentation map. This enables FCN to provide pixel-level predictions, accurately capturing fine-grained details and boundaries in the segmented regions. It also has the ability to handle variable-sized inputs. Traditional CNNs require fixed-size inputs, whereas FCN can accept images of arbitrary dimensions. This flexibility is particularly beneficial for this study as it allows for the segmentation of images with varying resolutions and aspect ratios, which is often encountered in real-world datasets.

The VGG-16 network is a CNN that has 16 layers, including 13 convolutional layers and 3 fully connected layers. The network was developed by the Visual Geometry Group at the University of Oxford and has been widely used in computer vision tasks, especially in image classification and object recognition. The input to the network is an RGB image of size 224x224x3, where the last number represents the red, green, and blue color channels. The network performs feature extraction on the input image through multiple convolutional and max pooling layers.

The first two layers of the network are convolutional layers with 64 filters of size 3x3 which are used for basic feature extraction on the input image. The third layer is a max pooling layer with a pool size of 2x2 and a stride of 2, which reduces the spatial size of the feature maps and helps to make the network more computationally efficient. The next two layers are convolutional layers with 128 filters of size 3x3, performing further feature extraction on the input image.

The sixth layer is another max pooling layer with a pool size of 2x2 and a stride of 2. Subsequent layers 7, 8, and 9 are convolutional layers with 256 filters of size 3x3, performing more complex feature extraction on the input image. The tenth layer is also the max pooling layer with a pool size of 2x2 and a stride of 2.

The following three layers are convolutional layers with 512 filters of size 3x3, which perform even more complex feature extraction on the input image. The fourteenth layer is another max pooling layer with a pool size of 2x2 and a stride of 2. The fifteenth and sixteenth layers are fully connected layers with 4096 neurons each, performing classification on the features extracted by the convolutional layers.

The final layer is a softmax layer with 1000 neurons, which outputs the probabilities for each of the 1000 possible classes in the ImageNet dataset. The VGG-16 network achieves a great performance on the ImageNet dataset. It is also commonly used in transfer learning, where the pre-trained model is fine-tuned on a smaller dataset to solve different tasks.

The VGG-16 network architecture has gained widespread recognition due to its complex and deep structure, which allows it to learn highly abstract features from the input image, leading to the achievement of high accuracy in image classification tasks.

2.3. Evaluation

To efficiently train out a relatively small dataset transfer learning was used. The implementation of transfer learning relies on a pre-trained model of the VGG-16 network [19] available from Matlab [20], which has been pre-trained on the ImageNet dataset [21]. The VGG -16 net was adapted into a fully convolutional network and their learned representations were transferred by fine-tuning to the segmentation task. FCN is pre-initialized using layers and weights from the VGG-16 network. A pre-trained VGG-16 was used as a feature learner, while the output masks are obtained from the fused feature maps from the fifth, fourth, and third pooling layers of VGG-16. The output from the fifth pooling of VGG-16 is 2× upsampled and fused with the fourth pooling in our network. Then, the combined map is 2× upsampled and again linked with third pooling. Finally, we perform 8× upsampling, which provides a segmented mask, by using both the local and global information to obtain the final mask.

The proposed network (VGG-FCN8s) is trained by using the Adam optimizer with an initial of 0.001, and exponential decay rates β1=0.9 and β2=0.99. To predict the class distribution, the Softmax function was performed on the network's output feature map. During the training procedure, we fed the samples into the network in batches, and each batch contained 8 images.

The proposed network is trained using 60% of the images from the dataset. The rest of the images are split evenly into 20% and 20% for validation and testing respectively. Before training, the whole dataset was always randomly shuffled.

Our hardware specifications include an Intel Core i5 processor i5-12600KF CPU @ 4.9 GHz, 16 GB of RAM memory, and an Nvidia GeForce RTX 3080 graphical processing unit (GPU).

3. Results

Once VGG-FCN8s was trained and tested, we utilize intersection over union (IoU), and boundary-F1 score (BFScore) to measure the performance with the test dataset (28 images) as commonly accepted evaluation methods for semantic segmentation tasks.

IoU represents the ratio of correctly classified pixels to the total number of ground truth and predicted pixels in that class, whereas meanIoU is the average IoU score of all classes in all images for the entire data set.

To minimize the impact of errors in the dataset with images having disproportionately sized classes, we also employ weighted-IoU which is the average IoU of each class, weighted by the number of pixels in that class.

The BF score reflects how closely each class's predicted boundary matches with the true boundary. MeanBF score indicates the average BF score for the class over all images. The average BF score of all classes in all images is also calculated.

In terms of the confusion matrix, those metrics can be defined as:

$$IoU = \frac{TP}{TP + FP + FN} \tag{1}$$

$$F_1 = \frac{2TP}{2TP + FP + FN} \tag{2}$$

Where TP, FN, and FP present the number of true positives, false negatives, and false positives, pixel predictions in the class.

The outcomes of the experiments carried out to evaluate the proposed network are presented in Table 1 and Table 2.

Table 1 Summary of the formatting rules

	MeanIoU (%)	WeightedIoU (%)	Mean BF score (%)
VGG-FCN8s	0.7784	0.9303	0.7919

Table 2 Intersection over union (IoU) and boundary F1-score (BF score) for each class obtained for the test dataset

	IoU (%)	Mean BF score (%)
Vineyard	0.9720	0.8510
Road	0.6073	0.5670
Other	0.6951	0.7111
Forest	0.9276	0.8053
Field	0.6899	0.5930

Judging from the experimental results, the proposed network could be appropriate for the task of semantic segmentation of satellite remote sensing images for AW source mapping. Although the classes with the largest number of pixels (forest and vineyard) had the better IoU and meanBF in comparison to the class with the lowest pixels (Road, Field, Other).

Considering that the goal of this research is to identify and categorize potential sources of AW obtained results are quite acceptable. Figure 3 presents some examples of the test results, which show that unseen images were successfully segmented into desired classes.

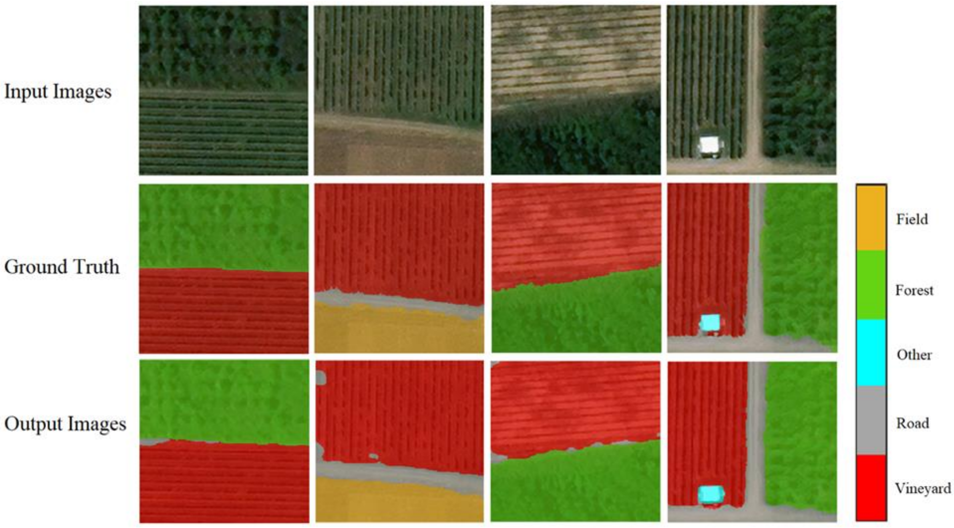

Fig. 3 The examples of the segmentation results on the testing images of the dataset

4. CONCLUSION

In this paper, a semantic segmentation model for the detection of potential agricultural waste sources using remote sensing images was proposed. The proposed model, VGG-FCN8s, used transfer learning with a pre-trained VGG-16 network that was fine-tuned for the segmentation task. By training the network on 60% of the dataset, and testing and evaluating the remaining images, a robust evaluation framework was established. The experimental results obtained in this study provide strong support for the acceptability of the proposed semantic segmentation model.

To assess the model's performance, widely accepted evaluation metrics for semantic segmentation, namely intersection over union (IoU) and boundary-F1 score (BFScore), were employed. The experimental results demonstrated notable achievements, particularly in mapping the target class of vineyard, with an IoU of 0.9720% and a mean BFScore of 0.8510%. These scores validate the model's capability to accurately segment vineyard areas, which was the aim of the first study case presented in this paper.

Furthermore, the performance evaluation extended to other classes present in the dataset. The forest class exhibited similarly high IoU and mean BFScore values, further highlighting the model's effectiveness in segmenting diverse land cover categories. While the scores for road, field, and other classes were slightly lower, the proposed model still showcased satisfactory segmentation capabilities across various class types.

The successful segmentation of previously unseen images into the desired classes confirms the robustness and generalizability of the proposed model. This outcome underlines its suitability for the task of semantic segmentation in the context of satellite remote-sensing images for agricultural waste source mapping.

To build upon the findings of this study, future work will involve expanding the training and testing dataset. The inclusion of a larger and more diverse dataset will provide a comprehensive assessment of the model's performance and enable a more thorough comparison with alternative methods of semantic segmentation. Such endeavors will contribute to further enhancing the accuracy and applicability of agricultural waste source mapping using remote sensing imagery.

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MAPIRANJE POLJOPRIVREDNOG OTPADA ZA PROIZVODNJU BIOGASA KORIŠĆENJEM POTPUNO KONVOLUCIONALNE NEURONSKE MREŽE I DALJINSKIH SATELITSKIH SLIKA

Sve veće generisanje otpada zajedno sa iscrpljivanjem prirodnih resursa dovelo je do potrebe za stvaranjem inovativnih pristupa za korišćenje različitih vrsta otpada kao potencijalnih energetskih i materijalnih resursa. Poljoprivredne aktivnosti prouzrokuju stvaranje velike količine poljoprivrednog otpada, koji, ako se njime ne upravlja na odgovarajući način, može dovesti do zagađenja životne sredine. Jedno potencijalno rešenje za efikasno korišćenje poljoprivrednog otpada je pretvaranje istog u biogas. Međutim, komercijalizacija ovog procesa zahteva potpuno razumevanje tipova i količina proizvedenog poljoprivrednog otpada. U ovom radu se predlaže upotreba potpuno konvolucione neuronske mreže (FCN), koja je brzo razvija sa napretkom veštačke inteligencije i koja je postala neophodna kada su u pitanju zadaci kao što je semantička segmentacija, detekcija objekata i klasifikacija slika. Ovaj rad predstavlja metod segmentacije slike zasnovan na dubokom učenju za *prepoznavanje polja vinograda, koja su značajan izvor poljoprivrednog otpada, korišćenjem daljinskih satelitskih snimaka. Predloženi pristup može značajno poboljšati pronalaženje i predviđanje izvora poljoprivrednog otpada i na taj način doprineti efikasnom i održivom korišćenju istog za proizvodnju biogasa.*

Ključne reči: *semantička segmentacija, poljoprivredni otpad, daljinska detekcija, proizvodnja biogasa, konvoluciona neuronska mreža*