Creation of a SaaS-System for Image Analysis in Agriculture Using Artificial Intelligence Methods

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Abstract

In various branches of agricultural production, including agriculture, some problems require the use of an intellectual approach. The authors develop a classification neural network, develop the server part of the application, as well as develop the user part of the application. The initial data set consists of 250 images, which is insufficient for high-quality training of a neural network. The main result of the created service is the ability, within the framework of the website, to receive an image that represents the original snapshot of the field and the layer mask superimposed on it. The use of the ANN classification type has shown that neural networks can reliably solve the problems of reclamation recognition of the state of agricultural fields. Advanced information technologies allow transferring resource-intensive calculations to the computing cloud. Computing in the cloud will help more convenient scaling of computing power when changing the formulation of the problem of intelligent classification. It is economically feasible to monetize a cloud service as a SaaS system.

Keywords

Agriculture · Image analysis · Artificial intelligence methods · SaaS-system

JEL Codes

C65 · C80 · C81 · C83 · C88 · C93 · Q12 · Q15

1 Introduction

Some problems require the use of an intellectual approach in various branches of agricultural production, including agriculture, crop production, and agricultural land reclamation. Various methods, models, tools, and technologies for assessing the economic efficiency of SaaS and decision-making support for choosing the method of its acquisition are considered in the monograph by K. N. Mitus et al. (2020). The mentioned monograph presents a SaaS in comparison with alternative options for its acquisition, as well as a decision support system (DSS) focused on the applied tasks of choosing the optimal way to purchase the software.

In agriculture, various developments and studies of the use of artificial neural networks (ANN) are known in various branches of agricultural production: in crop production (artificial intelligence-controlled greenhouses, robots for harvesting, etc.), in land reclamation (processing satellite images of agricultural fields, soil conditions, agricultural landscapes, etc.), and animal husbandry. Artificial intelligence (AI) is used where the use of classical mathematical methods of decision support is not enough, but intellectual analogs of human cognitive abilities are required. Such an approach can solve even global problems—ensuring the food security of the Earth's population, increasing the stability of yields by increasing the level of automation, revealing hidden patterns of crop formation, etc.

Deep ANN is a kind of nonlinear mathematical model. The software or hardware implementation of ANN copies the structure and functioning of neural networks of biological organisms in terms of the interaction of many of their nerve cells. In a mathematical sense, each artificial neuron (AN) performs a nonlinear transformation of the vector X of the signals at the input to AN into the vector Y of the output using the so-called activation function. The ANN structure is formed by the following types of AN, combined into layers:

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- Input (provide external information representing a set of values of input variables);
- Output (provides the return of output variables—control or generated predictive signals)
- Intermediate "hidden" layers of neurons that implement internal data transformation functions.

Therefore, a deep ANN contains at least three functional layers. Starting from the second layer, including the output layer, neurons are informationally connected to all elements of the previous one.

The increase in computer performance has led to the intensive development of the level and capabilities of ANN. In 2009, the computer giant IBM demonstrated a model of a cat's brain, but its performance turned out to be 650 times slower than the natural brain (Ananthanarayanan et al., 2009).

The basis of ANN application is the possibility of neural network training. The so-called "deep learning" uses a multilayered set of nonlinear filters that provide transformations at different levels of abstraction to extract the selected features. Approximately in the mid-2000s, the power of computers made it possible to train sufficiently large neural networks by organizing calculations on the GPU, and sufficiently large data sets were formed. Simultaneously, thanks to the publications of Hinton et al., an effective method of deep learning was proposed in the field of ANN theory, in which each layer of the network was trained separately using a limited Boltzmann machine, and then the backpropagation method was used (Deep learning, 2022).

Groups of researchers from Microsoft, Intel, and Tencent (Wageningen University, the Netherlands) conducted experiments on growing cucumbers indoors in fully automated greenhouses with full AI control over production (Wageningen University & Research, 2018). The results were compared with those obtained by experienced agronomists as a control. The Microsoft group achieved higher results.

Neural network technologies have found applications for the automation of robotic harvesting (e.g., strawberries). Nvidia robots are equipped with 3D cameras, with the help of which berries are isolated in the image using AI based on convolutional neural networks (CNN). Special algorithms evaluate the degree of fruit maturity. Then the robot, using an automatic "manipulator arm," cuts the ripe fruits and removes them from the bush. It should be noted that solutions based on traditional computer vision methods did not give the result achieved thanks to convolutional neural networks. Since training such networks using a central processing unit (CPU) requires additional computing resources, Nvidia developers use powerful additional technical solutions Jetson TX1/TX2. The authors of the publication note (itmanager85, 2021) that "robotization reduces the cost of final products and that, in particular, agriculture will completely change in the near future, thanks to such high technologies."

In 2018, researchers from the Sydney State University published an article (Padarian et al., 2019) on the results of humus assessment using deep neural network algorithms. The purpose of the study was to simplify soil mapping using CNN. The training was conducted on a small sample collected manually from the soil data of Chile. The neural network approach used showed fewer errors than the others. As positive aspects of the published work, the authors note the ability to consider the correlation of depths, the flexible architecture used in CNN, and the possibility of explicitly obtaining spatial information (Padarian et al., 2019).

Microsoft engineers are working with ICRISAT scientists to use AI to determine the optimal landing time in India (Onbillion, 2017). The application using Microsoft Cortana Intelligence Suite also allows evaluating the soil condition for which it recommends the required fertilizers. The program involved 175 farmers from 7 different villages. They started sowing after receiving a recommendation SMS notification. As a result, the harvest exceeded the traditional one by 30–40%.

ANN can also be used to solve other tasks in agricultural production. Within the crop production framework, neural networks can solve problems of recognizing weeds and diseased plants. When training and using ANN, it is very important to collect, form, and mark up training and test samples that are input data. Various issues of designing and using subject-oriented databases in agricultural production sectors, including agriculture, were considered by L. A. Zinchenko, V. M. Kureychik, V. G. Redko, and other scientists (Zinchenko et al., 2011).

2 Methods and Materials

The research aims to develop a cloud service on a classifying neural network. The study in the article is carried out in the context of the following tasks:

1. To develop a classification neural network;
2. To develop the server part of the application;
3. To develop the user part of the application.

The initial data set consists of 250 images, which is insufficient for high-quality training of a neural network (Rogachev et al., 2019).

To increase the original dataset, various data augmentation methods were used, including image mirroring and changes to the angle of inclination of the image in 10–180 degrees.

Another way that allowed expanding the dataset was adding incorrectly recognized images from those that were not originally included in it. The total size of the dataset was 6500 images.

For acceleration, training was performed on a GPU using CUDA. This was achieved by using a GPU based on the Nvidia RTX 2080TI chip, the CUDA Toolkit 11.4 library, and the Pytorch framework that supports the library (Nicely & Kraus, 2021).

3 Results

3.1 The Architecture of the Developed Network

According to the recommendations given in the Sik-ho Sung review (Tsang, 2018), ResNext 101×16 was chosen as the architecture. Preliminary tests were carried out on ResNext101×8 and ResNext101×32. ResNext101×8 gave lower accuracy, and ResNext101×32, without increasing accuracy, slowed down the learning algorithm. Other architectures were not considered in the development of the prototype.

A feature of the ResNet architecture is the parallel training of convolutional layers and the combination of the initial data of the block of network layers with its result.

Let us take a closer look at the main types of layers used in high-precision neural networks.

a) Convolution Layer

N: Batch size (Number of images in 4D tensor)
F: number of filters in the convolution layer
H/W: image height/width (usually H = W)
H'/W': collapsed height/width
Stride: The number of pixels that will move the sliding convolution window.

The Convolutional Layer is the main building block of the Convolutional Network, which does most of the computational work (Stanford Courses, n.d.).

b) Fully Connected Layer.

The input data is a four-dimensional tensor. A tensor consists of measurements:

H—height, W—width, Depth—depth, Batch size

Direct distribution:

1. Has three inputs (input signal, weight, and bias);
2. Has one output.

Backpropagating:

1. Has one inlet (outlet), which is the same size as the outlet;
2. Has three (dx, dw, and db) outputs.

c) Rectified-Linear unit Layer (ReLU)

The ReLU layer will apply the function to all elements of the input tensor without changing its spatial or depth information (Agarap, 2018; Brownlee, 2019).

ReLU is just a type of activation function possessing the following features:

- Easy to calculate (forward or backward propagation);
- Less affected by fading gradients on deep models.

The downside is that neurons can die irreversibly if we use a high learning rate.

3.2 Training Developed by CNN

The training took place on a pre-trained model on ImageNet, by retraining the classifier. The following classes for training were selected:

1. Good field;
2. Problematic field;
3. Unseeded field or not field.

The original image size is 255×255 px. Since the training occurred on a pre-trained model, it was possible to change its resolution.

The Adam algorithm was chosen as the optimizer. The step for training was 0.003. The steps were also tested in the range from 0.001 to 0.1; the most successful option was 0.003; with a lower value, more training epochs were required; with a higher value, the network quickly achieved overfit.

3.3 Network Results

The network results in a class for a 256×256 px image. However, the original images are images of fields of several thousand by several thousand pixels, so we cut the image into parts of 300 px and recognize it separately, then form a layer mask and overlay it on the original image.

3.4 Server

1. REST (Representational State Transfer) and web-socket API (application programming interface) for client interaction with the neural network;
2. Serving static files to the client (layout, styles, scripts).

REST is an architectural style of the interaction of components of a distributed application in a set API is a description of the ways in which one computer program can interact with another program. The following technologies were used for implementation:

1. Python—for interacting with the network;
2. Node.js—for SSR;
3. Web-sockets—as an additional technology for exchanging data with a client.

3.5 Client

The client is implemented as a SPA (single page application) in React js + Redux. Communication with the server is organized through web sockets as middleware for Redux. The use of web sockets is due to the display of processing progress in real-time.

4 Discussion

The main result of the created service is the ability, within the framework of the website, to receive an image that represents the original snapshot of the field and the layer mask superimposed on it. A visual color scheme has been adopted, according to which the red zones do not indicate agricultural fields and areas of non-sown fields but translucent red zones—problem areas of agricultural fields.

The results can be used in various ways for analysis by experts and the use of results by third-party services. Testing of the classification network has shown that neural networks can successfully solve problems of recognizing the state of fields (Alzubaidi et al., 2021; Kujawa & Niedbała, 2021; Melikhova & Rogachev, 2019). Comparing the results obtained with previous versions, it turned out to achieve a 10% increase in accuracy. This also leads to creating a service that users can interact with (Rogachev et al., 2020; Tokarev et al., 2020). However, this approach has several problems: linear stump load and low border accuracy. To solve these problems, we plan to switch to segmentation-type networks.

5 Conclusion

The conducted research allowed us to formulate the following conclusion.

1. The use of the ANN classification type has shown that neural networks can reliably solve the problems of reclamation recognition of the state of agricultural fields.
2. Advanced information technologies allow transferring resource-intensive calculations to the computing cloud.
3. Computing in the cloud will help more convenient scaling of computing power when changing the formulation of the problem of intelligent classification.
4. It is economically feasible to monetize a cloud service as a SaaS system.

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Data availability The following dataset is attached to the article: https://doi.org/10.6084/m9.figshare.20383002

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