DOI: 10.12731/2227-930X-2018-1-11-26
UDC 004.021

MACHINE LEARNING METHODS IN DIGITAL AGRICULTURE: ALGORITHMS AND CASES

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Ensuring food security is a major challenge in many countries. With a growing global population, the issues of improving the efficiency of agriculture have become most relevant. Farmers are looking for new ways to increase yields, and governments of different countries are developing new programs to support agriculture. This contributes to a more active implementation of digital technologies in agriculture, helping farmers to make better decisions, increase yields and take care of the environment. The central point is the collection and analysis of data. In the industry of agriculture, data can be collected from different sources and may contain useful patterns that identify potential problems or opportunities. Data should be analyzed using machine learning algorithms to extract useful insights. Such methods of precision farming allow the farmer to monitor individual parts of the field, optimize the consumption of water and chemicals, and identify problems quickly.

Purpose: *to make an overview of the machine learning algorithms used for data analysis in agriculture.*

Methodology: *an overview of the relevant literature; a survey of farmers.*

Results: *relevant algorithms of machine learning for the analysis of data in agriculture at various levels were identified: soil analysis (soil assessment, soil classification, soil fertility predictions), weather forecast (simulation of climate change, temperature and precipitation prediction), and analysis of vegetation (weed identification, vegetation classification, plant disease identification, crop forecasting).*

Practical implications: *agriculture, crop production.*

Keywords: *digital agriculture; machine learning; data science; big data; precision farming.*

МЕТОДЫ МАШИННОГО ОБУЧЕНИЯ В ЦИФРОВОМ СЕЛЬСКОМ ХОЗЯЙСТВЕ: АЛГОРИТМЫ И КЕЙСЫ

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Обеспечение продовольственной безопасности является важной задачей многих стран. В условиях роста населения Земли вопросы повышения эффективности сельского хозяйства становятся наиболее актуальными. Фермеры ищут новые способы повышения урожайности, а правительства разных стран разрабатывают новые программы поддержки сельского хозяйства. Это способствует более активному внедрению цифровых технологий в сельское хозяйство, помогая фермерам более эффективно принимать решения, увеличивать урожайность и заботиться об экологии. Центральное место здесь занимает сбор и анализ данных. В области земледелия данные могут собираться из разных источников и содержат в себе полезные закономерности, выявляющие потенциальные проблемы или возможности. Чтобы извлечь пользу из данных, они должны быть проанализированы с помощью алгоритмов машинного обучения. Такие методы точного земледелия позволяют следить за отдельными частями поля, оптимизировать расход воды и химикатов, а также оперативно выявлять проблемы.

Цель: *обзор алгоритмов машинного обучения, применяемых для анализа данных в сельском хозяйстве.*

Методология проведения работы: *обзор релевантной литературы, опрос фермеров.*

Результаты: *выявлены релевантные алгоритмы машинного обучения для анализа данных в сельском хозяйстве на различных уровнях: анализ почвы (оценка состояния почвы, классификация почвы, прогнозироваие плодородности почвы), прогноз погоды (имитация смены климата, прогноз температуры и осадков) и анализ состояния растительности (идентификация сорняков, классификация растительности, выявление болезни растений, прогнозирование урожайности).*

Область применения результатов: *сельское хозяйство, растениеводство.*

Ключевые слова: *цифровое сельское хозяйство; машинное обучение; наука о данных; большие данные; точное земледелие.*

Introduction

Data collected from agricultural fields with the help of soil sensors or unmanned aerial vehicles need further processing and analysis to identify useful patterns. Knowledge extracted from the data can be an important basis for making business decisions. Timely decision-making in agriculture can reduce the damage from possible problems and increase the yield in the future. The advantage for the farmer is to reduce costs and increase future profits. There are many algorithms for the analysis of data, and it is necessary to consider the specifics of the domain for choosing algorithms.

Survey of farmers

The study involved 42 farmers from the Astrakhan region (Russia) at the age of 18 or above. The questionnaire was created on the basis of the research objective; literature review was also considered. The questionnaire was used in paper and electronic form, in which the purpose of the study is indicated additionally.

Data from the questionnaire used in this study were considered for the selection of algorithms used in agriculture. The results showed that farmers are interested in obtaining additional insights at the stages of sowing and growth (see Figure). The data available for these stages are soil condition (including temperature, humidity, salinity) and digital images in high resolution with additional metadata (the images obtained with the drone also contain geographic coordinates). This narrows the choice of algorithms within the framework of this study.

Three types of tasks were selected for this study: soil condition and soil type classification, climate conditions simulation and weather forecast, vegetation status analysis and crop forecasting.

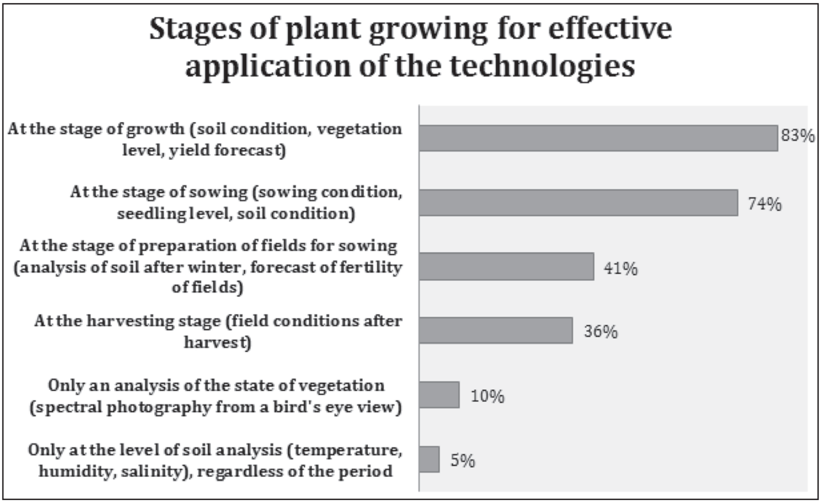

Fig. Stages of plant growing for effective application of the technologies

Algorithms for soil analysis

A type of tasks that may require the involvement of the algorithm is a classification of the soil type, an assessment of the soil state parameters, and the forecasting of soil fertility. Popular algorithms that can help achieve this goal are Decision Tree, k-Nearest Neighbours, and Naive Bayes algorithms. It should be noted that the choice of algorithms depends on the type and amount of available data (parameters).

An overview of some methods and tasks of analysing the state of the soil is presented in Table 1.

Table 1.

Soil tasks and methodology

Type of task	Methodology	Reference
Soil salinity evaluation	Linear Regression (paired t-test; significance test for regression parameters; temporal mean shift test)	[6]
Prediction of soil humidity	Regression Analysis; Genetic Programming	[13]
Soil water retention	k-Nearest Neighbour	[19]

Type of task	Methodology	Reference
Soil classification	Naive Bayes	[4]
	Recursive Binary Classification Trees	[2]
Prediction of soil fertility	Decision Tree	[11]

Case 1. Soil classification

In agriculture, the type and quality of the soil directly affects yields. The same plants can grow differently in different types of soil. In addition, crop, water and fertiliser monitoring strategies also depend on the type of soil. Classification of soil types is the basis for soil mapping, which is the benchmark for the farmer. One of the ways of soil classification is the use of Naive Bayes classification algorithm.

Naive Bayes classification technique for soil classification was used in India, Chittoor District in Rayalaseema region of the Indian state of Andhra Pradesh [4]. The source of the data was data from the soil databases of a local college, Department of Soil Sciences. Information on the most common types of soil was collected additionally, and the Unified Soil Classification System was used as a basis for classification. Soil data also included indicators of humidity, temperature and salinity of the soil, which can be collected with the help of soil sensors. Standard methods of statistics were expensive and time consuming, and Naive Bayes classifier showed its advantages.

The Naive Bayes classifier is based on the Bayes theorem and operates with a probabilistic approach. Based on the initial dataset, Naive Bayes classifier can be trained and used further for classification purposes. It requires a relatively small set of trained data to evaluate the required parameters [22, p. 85].

Dealing with data includes the following steps: data collection, data cleaning and checking, data formatting, data coding, analysis, and interpretation. WEKA software and Excel were used for the data processing and analysis. The results of the analysis showed a good level of classification (the instances were 100% classified). A comparison of Naive Bayes classifier with Decision tree (C4.5) and Bayesian Network has shown the advantage of Naive Bayes in terms of time costs and lower values of evaluation characteristics (Mean Absolute Error, Relative Absolute Error, Kappa Statistic, Root Mean Squared Error). Additionally, the Naive Bayes classifier showed a more accurate Normalised Expected Cost.

Case 2. Prediction of soil fertility

The soil productivity in agriculture depends, among other things, on the fertility of the soil. Soil fertility can be determined on the basis of soil characteristics (including moisture level and salinity level) and data on these characteristics can be collected using soil sensors. An accurate and effective model for predicting soil fertility can help a farmer correctly distribute crop planting and predict crop yields for the season. Decision Tree algorithm can underlie one of such prediction models. It was implemented and tested by researchers from India [11].

The data source for the analysis was datasets from a private soil laboratory in Pune District, India. Such data contains soil condition attributes and their corresponding values (10 attributes and 1988 instances). Soil fertility class is determined by qualitative characteristics: from very low and low to high and very high.

To build the model, the following algorithms of the decision tree family were used: C4.5 algorithm (statistical classifier, NBTree (decision tree with Naive Bayes classifier at the leaves)), and SimpleCart (non-parametric decision tree). Evaluation and comparison of these algorithms for this task were made on the basis of the accuracy and Error Rate using the 10-fold cross validation technique. C4.5 algorithm showed better accuracy and performance.

For this type of task, the attribute selection technique helps remove irrelevant attributes from the model and increase its accuracy. For this case, the accuracy of the model was 93.2%. To increase the accuracy, a boosting technique was also applied. This technique helps to redistribute weights from incorrectly identified instances to correctly ones [25, p. 23]. In this case, the accuracy of the model increased to 96.7%.

Thus, the decision tree algorithm can do well with the task of predicting soil fertility with the opportunity of improving model accuracy with attribute selection and boosting techniques.

Algorithms and techniques for weather forecasting

Weather conditions play an important role in the favorable growth of the crop in agriculture. The ambient temperature, precipitation level, wind speed can not only influence the growth of plants, but also make adjustments to the farmer's work in terms of its effect tillage. The two main sources of information on climate conditions are regional and federal online resources for monitoring and forecasting the weather (can be accessed on the Internet) and own meteorological station installed directly in the work area.

Weather station in comparison with other weather services allows more accurate measurement of climatic data (from the geographical point of view) and use this data to forecast weather in the region. Moreover, forecasts can be built and adjusted with the required precision in real time and this can help the farmer to take action quickly if necessary. In addition, the forecast of precipitation and ambient temperature can be additional factors for making decisions on watering plants or applying fertilisers.

An overview of some methods of weather forecasting is presented in Table 2.

Table 2.

Weather forecasting tasks and methodology

Type of task	Methodology	Reference
Simulating climate change scenario	k-Nearest Neighbour	[23]
Prediction of daily weather	k-Nearest Neighbour	[3]
Atmospheric temperature prediction	Support Vector Machines	[21]
	Ensembles and Bayesian Model Averaging	[8]
Precipitation prediction	Neural Network Models	[16]; [18]
	Support Vector Machines	[20]
	Ensembles and Bayesian Model Averaging	[8]
	Decision Tree, Artificial Neural Network, and Support Vector Machines	[12]

Case 3. Prediction of daily weather

Agriculture, of course, depends on weather conditions. The forecast of daily weather for this reason must be accurate (geographically localised) and timely for quick decision-making by the farmer. Possessing mechanisms for collecting meteorological data and an array of historical weather data, the farmer is able to use algorithms for short-term weather forecasts. One such example is the use of the k-Nearest Neighbour algorithm for prediction of daily weather [3].

K-Nearest Neighbour algorithm uses a historical set of weather observations as a basis and finds similar patterns in them. The assumption that historical data for previous years affect the weather indicators in the target year underlies this method. The algorithm selects a specific number of days, the parameters of which are similar to the current indicators and uses them to build the forecast for the next day.

The initial data used to analyse and validate the algorithm are historical weather data from 16 locations in the US, Burkina Faso, Iran, and the UK. Information on the level of radiation, rainfall, maximum and minimum temperature for each day was used in the model. Additionally, the model based on the K-Nearest Neighbour algorithm assumes that the data is recorded only for a part of the year (for example, the first 100 days), and the following days are not investigated and need a prediction. In this situation, the model can find the best combination on the historical data. Weather data is available, for example, only for the first 100 days, and the model calculates the Euclidean distance (this is used as the measure of distance) between the values of the current year and historical data for the same period (the first 100 days of each year). The year in which the selected distance measure is the minimum is considered best match and used to predict new values.

Software product was developed based on this approach. Estimating the predicted and observed data based on the Mean Square Difference (MSD) and Mean Absolute Scaled Error (MASE) values showed the reasonable accuracy of this approach. More historical data implies an increase in the chance of finding the right match and building a more accurate forecast.

Case 4. Precipitation prediction

The level of precipitation and their forecasting can play a key role in agriculture during the planting, growing, and harvesting stage. Some crops, for example, may need less water, or the farmer can set a watering schedule and water management depending on the level of precipitation. Precipitation can be predicted using the Support Vector Machines technique. Researchers from Spain used the Support Vector Machines method for accurate daily precipitation prediction and compared this technique to Decision Trees, k-Nearest Neighbour Classifier, Extreme Learning Machine, and Multi-layer Perceptron [20]. This problem was considered as a classification problem.

Data from Madrid-Barajas International Airport weather station were used in this case. The data structure included the following parameters: total precipitable water, equivalent potential temperature, humidity, temperature, wind speed, wind direction, convective available potential energy, and convective inhibition. METAR (Meteorological Terminal Aviation Routine Weather Report) and SPECI (Special Reports) meteorological reports were also used in this study. Support Vector Machines method was tested using two approaches with measurements precipitation by rain gauge (rain indicator) and using observation data from the airport.

The datasets contained meteorological data for the period 2009-2010 from intervals of 20 minutes between readings. The data were divided into training and test samples (80% and 20% respectively) and the models were built and evaluated on this basis. Support Vector Machine technique showed good performance compared to other methods listed above. AUC metric and ROC curve were used to compare the performance of different methods.

Algorithms and techniques for vegetation analysis

At the stage of crop growth, many problems can arise, and it can adversely affect yield results. This includes poor germination, arid zones, many weeds, plant diseases. One of the most effective ways of monitoring the state of vegetation is to survey agricultural fields from the air using satellites or unmanned aerial vehicles. There are also alternative ways to do it. This is, for example, manual inspection of fields by a person. But this method contains three significant drawbacks: the possible inattention of the observer, a large expenditure of time and money for large field sizes. Using unmanned aerial vehicles to collect data on the state of vegetation allows to obtain high-resolution digital images. With the help of special cameras (for example, multispectral or thermal) and GPS sensors it is possible to obtain more complete information about the object of observation with the indication of geographical coordinates.

Digital images can be further processed and analysed using machine learning algorithms. Existing methods allow to identify, for example, the problems of crop growth and to forecast yields. The techniques of image processing in agriculture include Neural Networks, Dual-segmented Regression Analysis, Colour Analysis, Fuzzy Logic, Support Vector Machines, Discriminant Analysis, Thresholding, Region Growing, k-Means Clustering, Bayes Classifier, Decision Tree Classification, Principal Component Analysis.

An overview of some methods of vegetation analysis is presented in Table 3.

Table 3.

Vegetation analysis tasks and methodology

Type of task	Methodology	Reference
Weed detection	Edge detection; color detection; classification based on wavelets; fuzzy logic; pixel classification based on K-means clustering and Bayes classifier; neural network based classification; principal component analysis	[24]
Vegetation classification	Initial segmentation; rule-based classification; re-segmentation; merging; nearest neighbour classification	[15]
	The conversion of NDVI time series from temporal space to Fourier space using a Discrete Fourier Transform. Principal component analysis.	[10]
Plant disease identification	Converting the RGB image of a plant into the H, I3a and I3b colour transformations. Four stages: image pre-processing (specification), image enhancement (filtration), image segmentation (identification), image post-processing	[5]

Type of task	Methodology	Reference
	K-means; SGDM matrix; color co-occurrence method; neural networks	[1]
Crop forecasting	Normalised Difference Vegetation Index (NDVI); correlation and regression analyses	[17]
	Harmonic analysis of NDVI time-series algorithm; decision tree classification; feature selection techniques (Chi-square test; correlation feature selection method; Wrapper's method with decision tree algorithm; combination of Information Gain and Ratio Gain methods); correlation analysis	[7]
	Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI); Multiple linear regression, Bayesian neural networks and model-based recursive partitioning models	[14]

Case 5. Crop forecasting

Forecasting the harvest is an important basis for business planning for the farmer. Having the necessary forecasts and calculated indicators, the farmer can pre-distribute the crop for future suppliers and adjust the logistics if necessary. Analysis of the state of vegetation of agricultural fields using machine learning methods can become a basis for such forecasts. Such a mechanism was used to predict crop yields on the Canadian Prairies [14]. The researchers used multiple linear regression, Bayesian neural networks, and model-based recursive partitioning models, as well as the methodology for applying the Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI).

The Agricultural Division of Statistics Canada for the Canadian Prairies and satellite data (MODIS-NDVI, MODIS-EVI and AVHRR-NDVI) were used to build forecast models. The datasets contained data for the period 2000–2011 for canola, barley, and spring wheat. MODIS (Moderate Resolution Imaging Spectroradiometer) and AVHRR (Advanced Very-High-Resolution Radiometer) are services that deliver images of certain Earth surfaces using space-born sensors in several spectral bands [9, p. 221]. NDVI and EVI are based on the principles of calculation based on different spectra. In addition, the statistics contained information on 40 Census Agricultural Regions, which were grouped using the hierarchical clustering method. This made it possible to simplify the construction and evaluation of crop forecasting models.

The algorithms indicated above were developed for the entire datasets, and their evaluation and comparison were based on a cross-validation method, the Mean Absolute Error (MAE), and the Skill Score (SS). All three models used showed a similar result. Nonlinear models showed a better result than the multiple linear regression model for barley. But the skill scores of multiple linear regression were higher than those of the other two models for canola and spring wheat. In addition, MODIS-NDVI proved to be a more effective predictor for yields compared to MODIS-EVI and AVHRR-NDVI. Nevertheless, the use of MODIS-EVI as an additional predictor to MODIS-NDVI can improve the quality of the forecast model.

Case 6. Plant disease identification

Plant diseases can negatively affect both the quality and quantity of the crop. It is important to identify such problems in time and make decisions on their elimination. A similar problem was solved by researchers from England who used an image-processing based algorithm to identify plant diseases [5].

As a data source, there were images in the jpeg format. Data from the universities of Iowa (images of maize and alfalfa) and Georgia (cotton and soya) and images from The International Network for the Improvement of Banana and Plantain (pictures of banana and plantain crops) were used. All images contained visual symptoms of plant diseases.

The image processing algorithm includes a conversion of the RGB image of a plant into the H, I3a and I3b color transformations and consists of four stages: image pre-processing (specification), image enhancement (filtration), image segmentation (identification), and image post-processing.

The procedure for measuring the success of the algorithm consisted in comparing the accuracy of the classifications of those images that were segmented manually with the same images, but classified automatically.

The test sample consisted of 20 images for five plant varieties. The images were evaluated and marked using a colour scheme (white for the infected area, black for the uninfected area). The final results of the segmentation algorithm showed a range of percent of matching 42–98.3%, and a range of percent of misclassification 2.2–35.5%. The algorithm was able to identify the problem areas (with plant diseases) in most images.

Conclusion

The most popular categories of algorithms used in digital agriculture are, on the one hand, supervised learning algorithms (an initial set of data is needed for learning the model). On the other hand, there are classification algorithms (for vegetation classification, crop forecasting, soil classification, etc.), clustering algorithms (for weed detection, plant disease identification, etc.), and neural networks, which are widely used in various agricultural tasks (in particular, image processing, crop forecasting). Using the right algorithm to solve a particular problem can help the agro-analyst and the farmer to extract more accurate insights from the collected data.

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