Comparison Between Electrical Impedance and Optical Spectroscopy for a Field Soil Analysis

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***Abstract*— In this paper, we performed a comparative analysis of the electrical impedance and optical methods performance for a field soil characterization. The study was optimized by reducing the texture variation and the influence of the unknown soil elements that are not in the focus of this research. The research dataset was created using pure soil from two agriculture farms and fertilized with fertilizers selected by farmers. The impedance spectrometer developed in our laboratory was used to perform the impedance measurements between 30 kHz and 14 MHz showing promising results. Optical measurements were performed within the ultraviolet-visible-near infrared (UV-VIS-NIR) range. The obtained results indicate that it is possible to perform low-cost soil analysis with high accuracy for a field fertilization analysis.**

Keywords- fertilizer analysis; soil analysis; impedance sensor; spectral analyser.

I. INTRODUCTION

The development of the fast and accurate soil characterizing sensors has been recognized as a crucial problem in nowadays agriculture. Several strategies with different degrees of success have been proposed to predict soil properties in a field [1][2]. Literature indicates a different degree of the accuracy for sensors that usually depends on the soil properties variation and sensor specifications [3]. Soil texture variation is the most common problem for agriculture sensors, leading to large datasets with an expensive chemical analysis that significantly increases the research cost [4]. Thus, the commercial AgroCares scanner is based on the reflectance spectroscopy and uses a large dataset to provide only brief information about soil nutrients, i.e., low, medium, and high. Therefore, a compromise between strategy and price must be found concerning the measuring time and accuracy. The most advanced technologies in agriculture use multi-sensor systems that include expensive ion-selective sensors [5]. This sensors type has high cost and requires a chemical solution that is not suitable for real-time measurement in a field. Alternative sensors, such as optical reflectometry and impedance spectroscopy, have relatively low cost and do not require chemical support. Unlikely, they are sensitive to soil moisture level, microelements variation, ambient temperature, humidity, etc. Optical reflectometry is the most common method mentioned in the literature that operates on the whole Ultraviolet-Visible-Near Infrared (UV-VIS-NIR) range.

Nevertheless, some researchers indicate the unstable performance of this method. Luleva et al. [6] showed the influence of the soil texture on the position of the potassium absorption centre. They also reported that samples with high clay content results in a smaller change in absorption. The electrical impedance method is less accurate for soil nutrients detection and is commonly used for soil moisture analysis or quantitative analysis when other components are neglected [7]. Pandey et al. [8] reported their results for soil-nitrates detection in a real-time application indicating the impedance method great potential for in-suite measurements.

Our research aims to integrate a low-cost solution suitable for real-time field applications with high accuracy. Therefore, the comparison between impedance and optical methods performance was studied. To minimize the influence of the texture and unknown microelements (that are not in the focus of this research), the fertilized soil's characterization was performed using soil from a field. The fertilized soil samples with different nutrition levels were achieved using only fertilizers defined by farmers. Following the literature recommendations, soil samples were prepared in the laboratory and measured using electrical impedance and optical methods. Finally, the classification-based validation approach for soil collected in two entirely different locations in Slovenia was performed to compare the methods' effectiveness. Due to the non-uniform soil properties, it is common to perform a set of measurements in different locations to reduce variability. Therefore, the final validation accuracy was achieved based on a set of repetitive measurements for each soil sample.

Section II describes research datasets, set-ups for electrical impedance and optical measurements, method for soil properties prediction using classification-based approach. Electrical impedance measurement was performed using laboratory designed soil spectrometer. This spectrometer is small and easy to use. Its impedance Application Specific Integrated Circuit (ASIC) was implemented by using the CMOS process. A programmed microprocessor enables the communication between ASIC and personal computer. Finally, results of the soil properties prediction are shown and discussed in Section III.

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II. MATERIALS AND METHODS

This section describes the research dataset and instruments used for soil measurements. All measurements were performed in the laboratory under controlled conditions. To eliminate the impact of external factors, the ambient temperature near 22℃ and relative humidity under 40% are kept constant.

A. *Dataset*

The research datasets, i.e., Dataset A and Dataset B, consist of soil samples collected from two different agriculture farms in Slovenia. The pure soil samples are collected from a 0-30 cm top-soil surface. Each sample is air-dried for one month, grounded, and then sieved through a 2-mm sieve to provide a dry base for experiments. Following recommendations in literature and farmers requirements, a simple system for nutrient-level classification and coding shown in Table I is created and used for model parameters learning. Using this system and chemical characteristics, codes for each soil sample were obtained with respect to the amount of phosphorus, potassium, and magnesium (see last columns in Tables II and III).

TABLE I. A SIMPLIFIED SYSTEM FOR SOIL NUTRIENTS LEVEL CODING.

Score, mg/100g	Grade
0 - 10	0
11 - 20	1
21 - 30	2
31 - 40	3
> 40	4

The commonly used agricultural fertilizers selected by farmers were used to prepare samples with a different nutrition levels. Each fertilizer was diluted in a deionized (DI) water and then mixed with an air-dried soil in various concentrations. Tables II and III provide information about soil chemical characteristics performed by a certified laboratory at the Agriculture Institute of Slovenia [9]. The chemical analysis results shown in tables indicate an entirely different fertilizer impact on the soil chemical properties, with an observable correlation between the added fertilizer concentration and nutrient change. Thus, a medium level of a nutrient in the soil corresponds to roughly 0.05% of fertilizer. A 0.1% concentration of fertilizer leads to a high level of a nutrient that is also confirmed in literature [10].

TABLE II. CHEMICAL CHARACTERIZATION OF THE SOIL SAMPLES FROM DATASET A.

Soil ID	Added fertiliser	P, mg/100g	K, mg/100g	M, mg/100g	Code
1	none	3.9	6.4	23	002
2	0.05% F1	14	6.4	24	102
3	0.05%P+0.05% F2	16	15	25	112
4	0.1%K	4.2	44	23	042
5	0.1% F1+0.1% F2	39	47	23	342
6	0.05% F3	7.8	14	22	012
7	0.1% F3	12	17	22	112

F1: Triple super phosphate (P2O5 -46%); F2: potassium sulphate (K2O - 50%); F3: Potassium phosphate (14% P2O5, 28%K2O, 2%MgO).

TABLE III. CHEMICAL CHARACTERIZATION OF THE SOIL SAMPLES FROM DATASET B.

Soil ID	Added fertiliser	P, mg/100g	K, mg/100g	M, mg/100g	Code
1	0.05%F1	18	13	25	112
2	0.05%F2	10	20	25	012
3	0.05%F3	11	15	29	112
4	0.05%(F1+F2+F3+F4)	23	23	30	222
5	0.1%F1	23	16	25	212
6	0.1%F3	11	16	34	113
7	0.1%F5	11	14	24	113
8	none	10	17	23	012

F1: calcium phosphate (P2O5 -26%, CaO - 40%); F2: potassium sulphate (K2O - 50%); F3: magnesium sulphate (MgO - 25%, SO3 - 50%); F4: potassium sulphate (K2O - 60%); F5: organic mass minimum 70%.

B. *Soil electrical impedance measurement set-up*

This paragraph describes the laboratory set-up for the measurement of soil samples. Measurements were carried out from the moist soil. Therefore, the dry soil samples were mixed with the predefined amount of the DI water (i.e., 60% of the dry soil sample base) to obtain soil samples with the same moisture level. The obtained soil samples were then placed in a 3D-printed holder with approximate dimensions of 20 x 10 x 10 mm (Figure 1). The soil holder was designed to hold small soil moisture samples of approximately 5 g.

The workspace set-up for impedance measurement is shown in Figure 1 that includes an impedance spectrometer interfaced with the personal computer (PC) for data processing and storage. The measuring process was controlled using a graphical user interface developed in Matlab software [11].

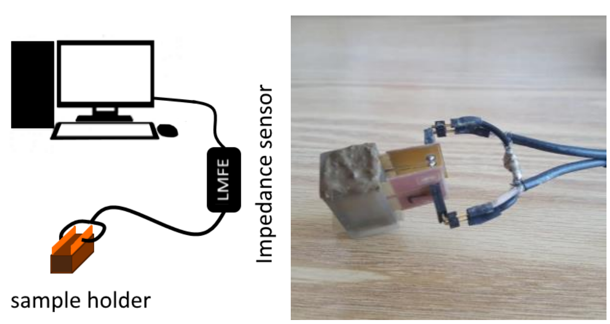

Figure 1. Photography of the set-up for electrical impedance measurement and sample holder with soil. (a) set-up workspace for measurement; (b) sample holder with the soil.

The impedance spectrometer's architecture is split into three main sections: analog, processing, and sensor. The Analog section measures soil electrical impedance. The spectrometer generates AC current with user-set frequency and sends it in the soil through sensor electrodes. The resulting imaginary and real components of the impedance are then digitized and send to the PC via the universal serial bus (USB).

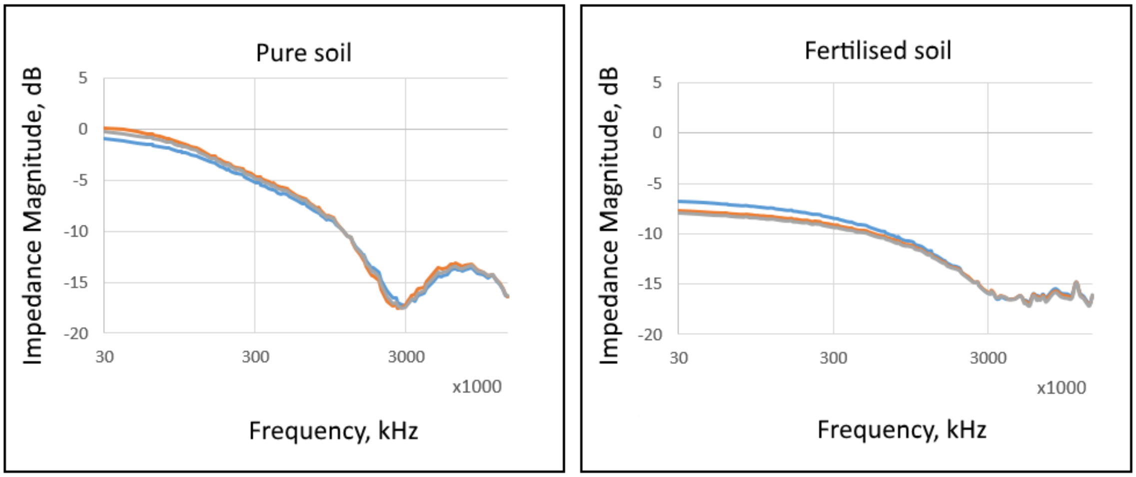

Figure 2. Impedance magnitudes of three pure soil sub-samples and three fertilized soil sub-samples respectively.

Spectroscopy measures resultant voltages when a constant current is applied at different frequencies. The 122 frequencies selected between 30 kHz and 14 MHz enable a good fit of the whole frequency domain's impedance signal. Figure 2 shows impedance magnitudes plots corresponding to three sub-samples of the pure soil and impedance magnitudes plots corresponding to three sub-samples of the fertilized soil over the selected frequency range. As expected, measurements of sub-samples collected from the same soil are very similar. A small deviation can be explained by non-ideal manual sample preparation that can be improved by an automatic sample preparation. As the frequency increased, the impedance of the samples dropped obviously. It can also be noted that the lower fertilizer content is associated with higher impedance amplitude. Our earlier research indicates that soil solutions' primary information can be achieved from impedance magnitudes alone [12] that is also observed for soil characterization in our study. Therefore, the only impedance magnitudes are used in the following analysis.

C. *Soil optical measurement set-up*

This paragraph describes the set-up for the light reflectance measurement. A deuterium-halogen light box was used as the light source. The light reflectance from the sample was measured by placing 5 g of air-dried sieved sample into a quartz glass petri dish three mm-diameter, as shown in Figure 3. The set-up includes a fiber-coupled spectrometer FCR-7UV200-2-ME from Avantes that is fixed perpendicularly to have a 3 cm distance between the probe and samples. The light from a light source is sent through six illumination fibers to the sample, and the reflection is measured by a seventh fiber in the center of the reflection probe tip. The AvaSpec-ULS2048CL-EVO-RS and AvaSpec-HSC-TEC perform the light measurement in the ultraviolet, visible, and near-infrared regions of the electromagnetic spectrum, i.e., 200-2500 nm. Spectra normalization was performed by dividing soil reflectance spectra by the white body reflectance spectra used here as a reference.

Soil spectral measurements were collected from seven randomly selected points for each air-dry sample. Figure 4 shows seven plots corresponding pure soil in the UV-VIS range and NIR range, separately. It can be seen that the UV range between 200 to 400 nm is less informative than the VIS range and does not provide any characteristic variations that can be seen visually. The normalized signal in the VIS range appears with a bias having shape variation and peaks appearance that can be characteristic for different soil properties. The obtained plots indicate good repetitiveness of the measurements corresponding to the same soil. The small variation between measurements can be explained by a non-uniform soil surface resulting in a reflectance angle variation.

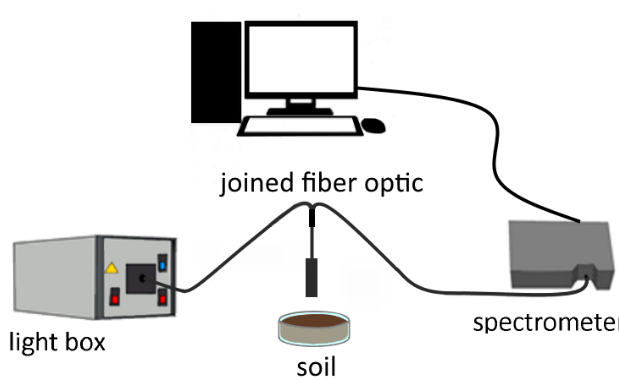

Figure 3. The experimental set-up for optical measurement

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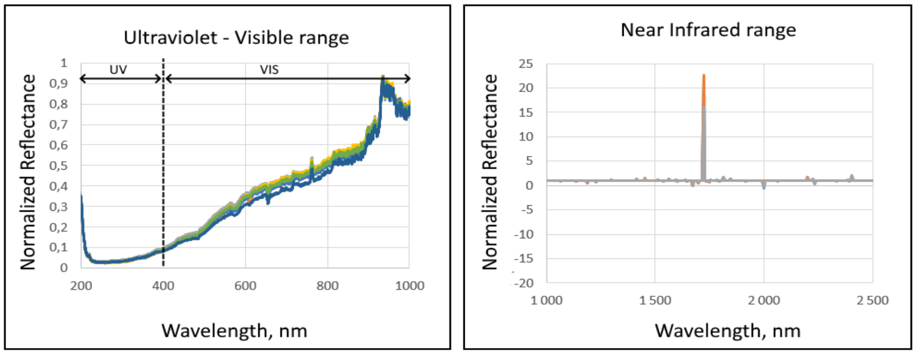

Figure 4. Normalized spectra plots obtained for pure soil in the UV-VIS range and NIR range.

D. Soil properties prediction

The principle of the soil's properties prediction is based on identifying the measurement from the research dataset. This measurement has shape variation as close as possible to the shape variation of the test measurement belonging soil, which characteristics need to be predicted. Then, chemical characteristics of the identified measurement are used to indicate the properties of the soil. The leave-one-out principle [13] is applied to validate the classification accuracy, where each sample is excluded from the dataset and used as a testing set. The rest of the samples are then joined in a training set.

The classification procedure consists of feature extraction and machine learning. Several feature extraction methods, such as' regionprops', moment invariants, etc., are proposed in the literature. However, each particular task requires a complex analysis to estimate the optimal features enabling the best classification of high-dimensional data. Thus, classification based on a principal component analysis (PCA) [14] is used in this research allowing the most optimal performance, where fixed threshold Th=0.2 was applied on the feature weights to reduce irrelevant features (Figure 5). The PCA maximizes the expected classification accuracy reducing feature vector. The decision tree procedure was used for machine learning to estimate parameters characterizing the training set [15].

III. RESULTS AND DISCUSSIONS

This section demonstrates the effectiveness of the electrical impedance and optical methods for identifying the soil samples in research dataset A and research Dataset B using a classification-based approach. Measurements were performed using set-ups described in Section II for electrical impedance and optical methods. Thus, 21 feature vectors corresponding to 7 soils from Dataset A and 24 feature vectors corresponding to 8 soils from Dataset B were obtained during electrical impedance measurement. During optical measurement, 49 feature vectors corresponding to 7 soils from Dataset A and 56 feature vectors corresponding to 8 soils from Dataset B were obtained. Tables IV and V show the results of the leave-one-out classification for research datasets with entirely different characteristics. Classification results from the corresponding optical method are shown separately for the UV-VIS range and NIR range to investigate their effectiveness for the soil properties prediction. As can be noted, the optical approach enables more accurate sample identification when the electrical impedance is less accurate. The incorrect identification of the soil samples with different amounts of the phosphorus can be observed. This can be explained by a small difference between measurements corresponding to pure soil and soil with added potassium fertilizer. In this research, it was observed that the impedance response of the phosphorus fertilizer is the smallest compared to other fertilizers under analysis. The NIR range showed results that are also less accurate than the VIS range. Therefore, it is possible to provide a characterization using only the VIS range.

Figure 5 shows the weights of the dataset values for different methods. The essential features for classification using the UV-VIS range are concentrated near the NIR range. Features corresponding electrical impedance magnitudes can also be easily observed and detected near the domain end. Therefore, using feature selection procedure it is possible to significantly reduce frequencies and wavelengths required for accurate analysis. The fixed threshold in our analysis was selected based on the visual inspection and enabled good delineation between informative and uninformative features. Nevertheless, for different set-up it is possible to detect threshold invisibly based on the statistical analysis of the all feature weight. For this purpose, the automatic Otsu method can be used [16].

TABLE IV. CLASSIFICATION RESULTS FOR DATASET A.

method of data capturing	P, mg/100g	K, mg/100g	M, mg/100g
El. impedance measurements	77%	71%	100%
UV-VIS range measurements	90%	84%	100%
NIR range measurements	90%	81%	100%

TABLE V. CLASSIFICATION RESULTS FOR DATASET B.

method of data capturing	P, mg/100g	K, mg/100g	M, mg/100g	
El. impedance measurements		75%	96%	100%
UV-VIS range measurements		80%	91%	93%
NIR range measurements		75%	92%	88%

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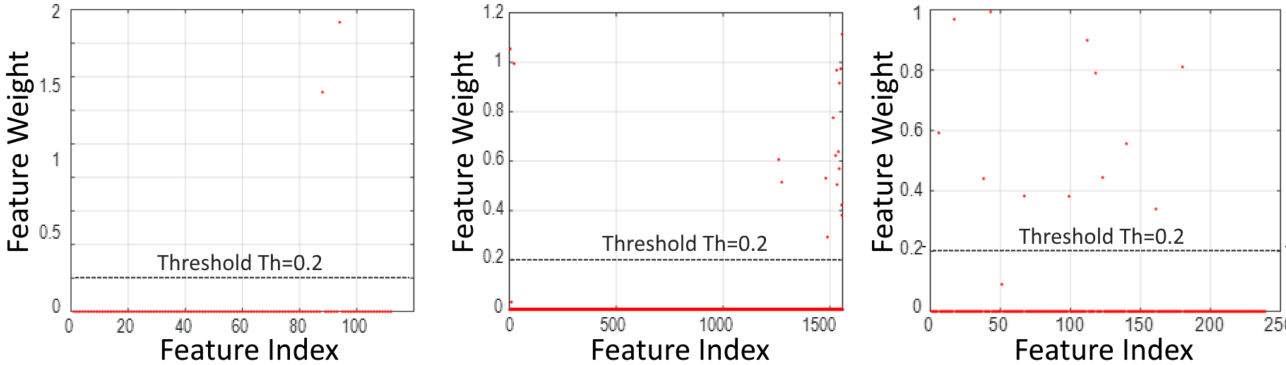

(a) (b) (c)

Figure 5. Feature weights corresponding (a) frequency domain, (b) UV-VIS range, and (c) NIR range

The classification results obtained for soils located in entirely different Slovenia locations indicate the potential of the sensors for a real-time field fertilization analysis. The difference between classification accuracy obtained for Dataset A and Dataset B can be explained by the fertilizer difference used in the analysis. Thus, a different chemical solution may have different influence on the measurements when performing measuring.

Due to the obtained results, it can be concluded that there is possible to obtain the low-cost sensor for soil fertilisation characterisation. Feature selection procedure significantly reduced the wavelength range and frequencies in our analysis without classification accuracy lost. Thus, the final price of the sensor would be also reduced.

All measurements were carried out under controlled laboratory conditions in order to perform accurate methods performance comparison. This is a critical step when selecting sensor for implementation. The atmospheric factors, such as rain and wind, has obviously significant influence on the methods that will be discovered in a future work.

IV. Conclusion

The results obtained in this research indicate the potential of both electrical impedance and optical method for accurate soil analysis and nutrients identification alone when performing characterization within a field. Due to the high sensitivity of the electrical impedance measurements to the various factors, such as texture, temperature, etc., it is critical to minimize their influence on the classification procedure. The feature extraction using principal component analysis enables detecting the most informative frequencies and wavelengths for a low-cost real-time sensor implementation. Only the VIS range for optical spectroscopy is required. The electrical impedance method in this research performs better for magnesium identification and less accurate for phosphorus due to the different impacts of the fertilizer on the measurements.

References

[1] A. Bah, S. Balasundram, and M.H.A. Husni, "Sensor Technologies for Precision Soil Nutrient Management and Monitoring", American Journal of Agricultural and Biological Science, vol. 7, pp. 43-49, 2012.

[2] G. Pajares, "Advances in sensors applied to agriculture and forestry", vol. 11, pp. 8930–8932, December 2011.

[3] V. I. Adamchuk, J. W. Hummel, and M. T. Morgan, S. K. Upadhyaya, "On-the-go Soil Sensors for Precision Agriculture.", Computers and electronics in agriculture, vol. 44, issue 1, pp. 71-91, July 2004.

[4] A. K. Rêgo Segundo et al., "A Novel Low-Cost Instrumentation System for Measuring the Water Content and Apparent Electrical Conductivity of Soils", Sensors, vol. 15, Issue 10, pp. 25546-25563, October 2015.

[5] W. S. Lee et al., "Sensing technologies for precision specialty crop production", Computers and Electronics in Agriculture, vol. 74, issue 1, pp. 2–33, 2010.

[6] M. I. Luleva, H. van der Werff, V. Jetten, and F. van der Meer, "Can infrared spectroscopy be used to measure change in potassium nitrate concentration as a proxy for soil particle movement?", Sensors (Basel), vol. 4, issue 4, pp. 4188-4206, 2011.

[7] U. Lazuardi and S. Rahmondia, "Low Cost Soil Sensor Based on Impedance Spectroscopy for In-Situ Measurement", AIP Conference Proceedings, American Institute of Physics, April 2015, vol. 1656, issue 1, pp. 040005(1-9), ISBN: 978-0-7354-1298-9.

[8] G. Pandey, R. Kumar, and R. J. Weber, "Real Time Detection of Soil Moisture and Nitrates Using On-Board In-Situ Impedance Spectroscopy", 2013 IEEE International Conference on Systems, Man, and Cybernetics, Manchester, 2013, pp. 1081-1086, 2013, doi: 10.1063/1.4917112.

[9] Agriculture Institute of Slovenia. [retrieved: October, 2020] Available online from: http://arhiv.kis.si/pls/kis/!kis.web?j=EN

[10] M. Sirsat, E. Cernadas, M. Fernandez-Delgado, and R. Khan, "Classification of agricultural soil parameters in India", Computers and Electronics in Agriculture, vol. 135, pp. 269 – 279, 2017.

[11] The Mathworks, Inc., Natick, Massachusetts. MATLAB version 8.5.0.197613 (R2015a), 2015.

[12] O. Chambers, A. Sešek, R. Ražman, J. F. Tasič, and J. Trontelj, "Fertiliser characterisation using optical and electrical impedance methods", Computers and Electronics in Agriculture, vol. 155, pp. 69-75, 2018.

[13] K. Anbumani and R. Nedunchezhian. Soft Computing Applications for Database Technologies:

Techniques and Issues. Hershey, PA: IGI Global, 2010. http://doi:10.4018/978-1-60566-814-7.

[14] Yang, W., K. Wang, and W. Zuo. "Neighborhood Component Feature Selection for High-Dimensional Data", Journal of Computers, vol. 7, issue 1, pp. 161-168, January, 2012.

[15] W. Y. Loh, "Regression Trees with Unbiased Variable Selection and Interaction Detection", Statistica Sinica, vol. 12, pp. 361–386, 2002.

[16] Nobuyuki Otsu. "A threshold selection method from gray-level histograms". IEEE Trans. Sys. Man. Cyber. Vol 9, issue 1, pp. 62–66, 1979.

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