Agricultural Research & Technology
Open Access Journal
ISSN: 2471-6774

Juniper Publishers
key to the Researchers

Research Article
Volume 25 Issue 2 - January 2021
DOI: 10.19080/ARTOAJ.2021.25.556307

Agri Res & Tech: Open Access J


# Advances in Real-Time Soil Fertility Determination

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**Submission**: January 15, 2020; **Published:**January 21, 2020

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**Abstract**

Rapid advances in sensor technology are enabling aggressive use of informatics in agriculture. This paper focuses on applying the newly developed soil electrical impedance spectrum sensor combined with artificial intelligence to predict soil fertility. The described method determines the type and amount of fertilizer to be used. The proposed sensor system is portable and fast enough for real-time measurements in the field using a slow-moving tractor. It is affordable, battery-powered and allows wireless data transmission to the farmer's soil database. Such a database allows the farmer to create a reliable fertilizer plan. The crop is of better quality because fertilizer is applied only where it is needed on the plot. The use of fertilizer is optimized, costs are reduced, and the environment is preserved. Many papers report more or less credible results on this problem, but they lack verification of real conditions in the field.

**Keywords:** Soil analysis; Real-time fertilization plan; Electrical impedance spectrum of the soil; Soil classificatory

**Abbreviations:** Application Specific Integrated Circuit (ASIC); Deionized (DI); Agriculture Institute of Slovenia (KIS); Principle of Component Analysis (PCA)

## Introduction

The diversity of soil conditions in terms of its moisture, composition, texture, and temperature makes soil analysis very difficult. The deterministic methods, such as chemical analysis, cannot be used in the field because it requires a chemical laboratory. It is time consuming, expensive and unreliable as it only relates to a particular soil sample. Dozens of soil samples must be collected and analyzed per acre. In the recent article [1], the authors described their vision about the future development of digital agriculture. They listed several possible sensors that would monitor the agricultural plot and collect a soil and crop status database below and above the surface. The analysis of this data would pave the way for the optimization of agricultural activities. Many methods have been described [2-4], but none are accurate enough or acceptable for real-time applications. We want to collect soil fertility results in a few seconds while driving the tractor over the field. In this section, we will briefly review some of the most promising soil characterization technologies. Optical methods were investigated using spectral analysis in both the visible and visible-infrared spectra, analyzing either reflectance or transmittance results. Our investigation of these methods did not meet our expectations. We tried an interesting approach to study the residual of tiny dried droplets of soil extraction fluid and found promising results. This approach is shown in Figure 1. Figure 2 shows the optical spectra of such a soil solution. Some other impressive results can be obtained under laboratory conditions, but field application is not feasible. Raman spectroscopy or mass spectroscopy analysis is too expensive and too slow for on the fly analysis. The non-contact methods using microwaves and terahertz waves are too expensive and not convincingly reliable. Unfortunately, these methods have not met the expected criteria. We need a better approach that is marketable and accepted by farmers. In our study, we decided to develop a sensor system that meets the following criteria for acceptance:

a. accuracy, reliability, and repeatability,

b. fast, on the spot, portable, battery-powered,

c. easy to use, robust and user-friendly,

d. low cost, and

e. ready for wireless communication.

The closest technology to meet the listed requirements seemed to measure and analyze the soil's electrical impedance spectrum. The soil electrical impedance spectrum method [4] is the most promising, but it requires significant extensions to meet the listed acceptance criteria. In the following sections we will describe these extensions.

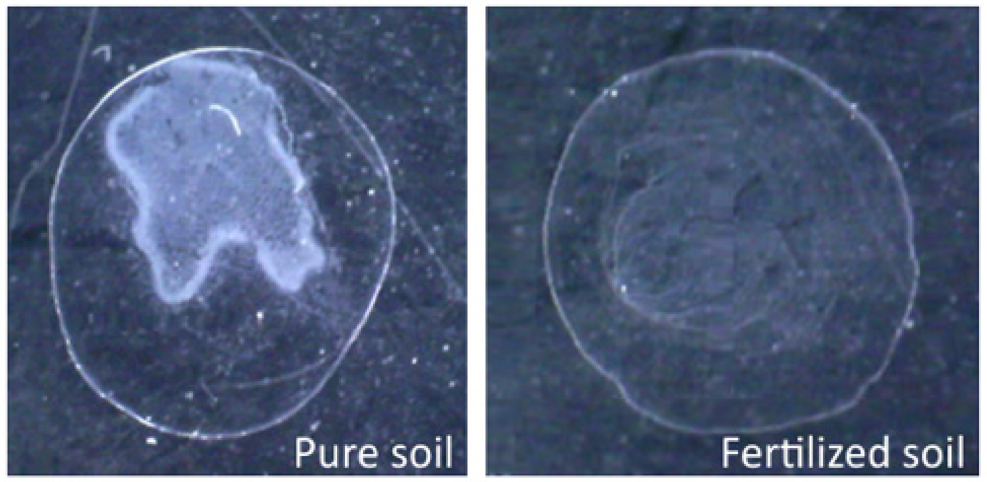


**Figure 1:** A dried droplet of soil solution on a hot plate for pure soil and the fertilized soil.

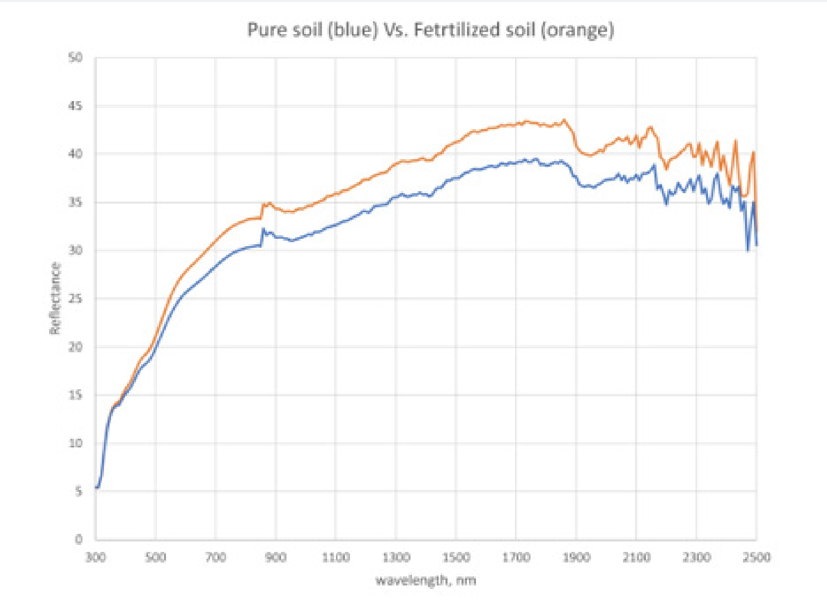


**Figure 2:** A spectrum of the reflected light of the solution of pure soil (blue) and the fertilized soil (orange).

## Materials and methods

In the field, the soil sample has unknown composition, texture, and moisture. These values significantly affect the soil spectrum and affect soil classification and fertilizer prediction accuracy. In laboratory experiments, these conditions are known and held constant. However, to classify an unknown soil sample, some additional soil parameters must be recorded. These are the relative soil viscosity, the temperature, the value PH and the DC resistivity. These values are used to pre-select a reference database for the classification algorithm. The resulting classification algorithm is then significantly improved. These improvements mean that the soil database of known chemical parameters must be expanded to include the listed parameters. Figure 3 shows the flow-chart of the classification algorithm procedure. Figure 4 shows a simplified schematic of the soil impedance spectrometer Application Specific Integrated Circuit (ASIC). It consists of a mixed-signal design of the front-end electronics, a programmable clock generator to excite the soil sample, and the signal processing unit to calculate the impedance's real and imaginary parts. Figure 5 shows


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the simplified interface diagram between the ASIC of the soil impedance spectrometer and the processing unit, like a personal computer or similar. Soil samples are collected from 0-30 cm soil surface and then prepared in the laboratory for characterization and classification. The soil samples were air-dried and sieved 2 mm. They were then mixed with the required amount of Deionized (DI) water to obtain a soil mass with the required viscosity. The amount of DI water is different for each soil and is estimated automatically. A certified laboratory performed a chemical analysis of all soil samples in the Agriculture Institute of Slovenia (KIS) [4]. The comprehensive characterization of each soil sample contains information on all common soil constituents, and only the analyzed nutrients are listed in Table I. Reading and storing the imaginary and real parts of signals corresponding to a soil sample or reference circle is performed using Matlab software. The Matlab script is created to read the controller Analog to Digital Converter (ADC) data and store it in a personal computer or database for further processing.

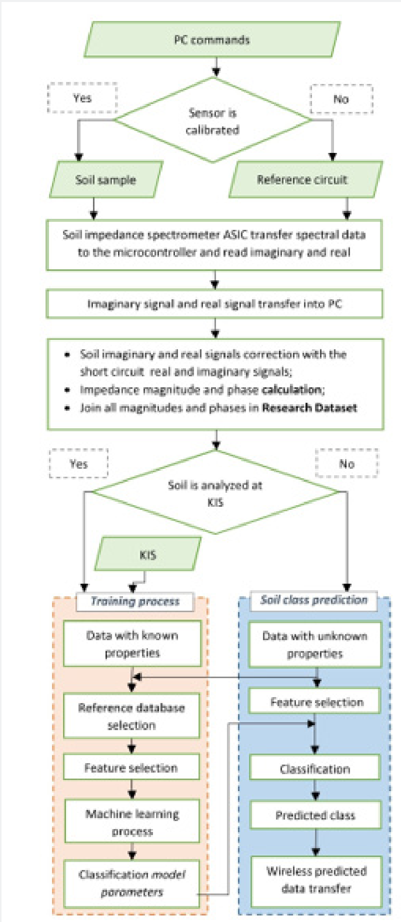


**Figure 3**: Flow-chart for soil analysis.

**Table 1:** Soil chemical analysis performed by a certified laboratory at the Agriculture Institute of Slovenia, KIS [4].

| Sample name | KIS ID | pH in KCl | P2O5* | K2O* | Mg* | OM | N |
|---|---|---|---|---|---|---|---|
| | | mg/100g | mg/100g | mg/100g | mg/100g | % | g/kg |
| Soil_1 | 3908/2018 | 7,6 | 3,1 | 32 | 6,9 | 5,8 | 3,4 |
| Soil_2 | 3909/2018 | 4,1 | 1,1 | 6,8 | 5,8 | 4,9 | 2,3 |
| ... | | | | | | | |
| 1KA | 0992/2019 | 6,6 | 6 | 19 | 30 | 2,4 | 1,4 |
| 2KA | 0993/2019 | 7,7 | 20 | 31 | 8,1 | 3,3 | 2,2 |
| 3KA | 0994/2019 | 7,5 | 34 | 39 | 13 | 5,5 | 3,5 |

*Phospurous-P2O5; potassium-K2O; magnesium-Mg


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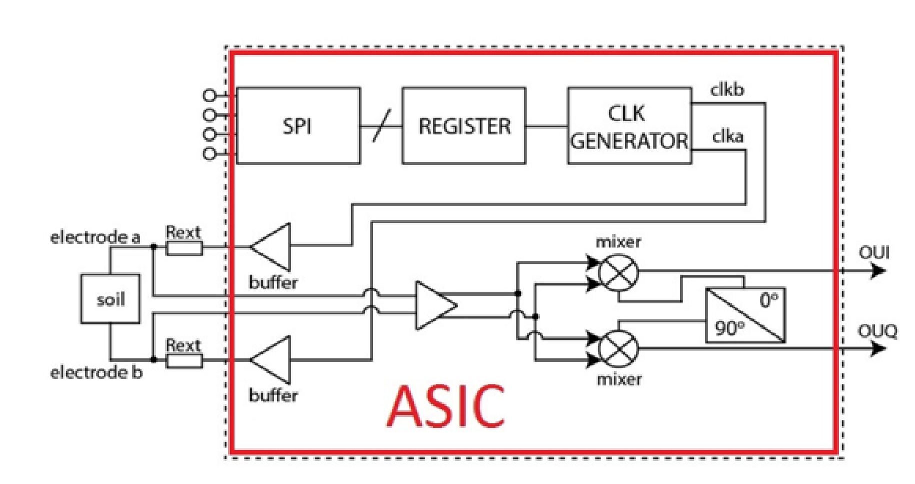


**Figure 4:** Simplified schematic of soil electrical impedance spectrometer.

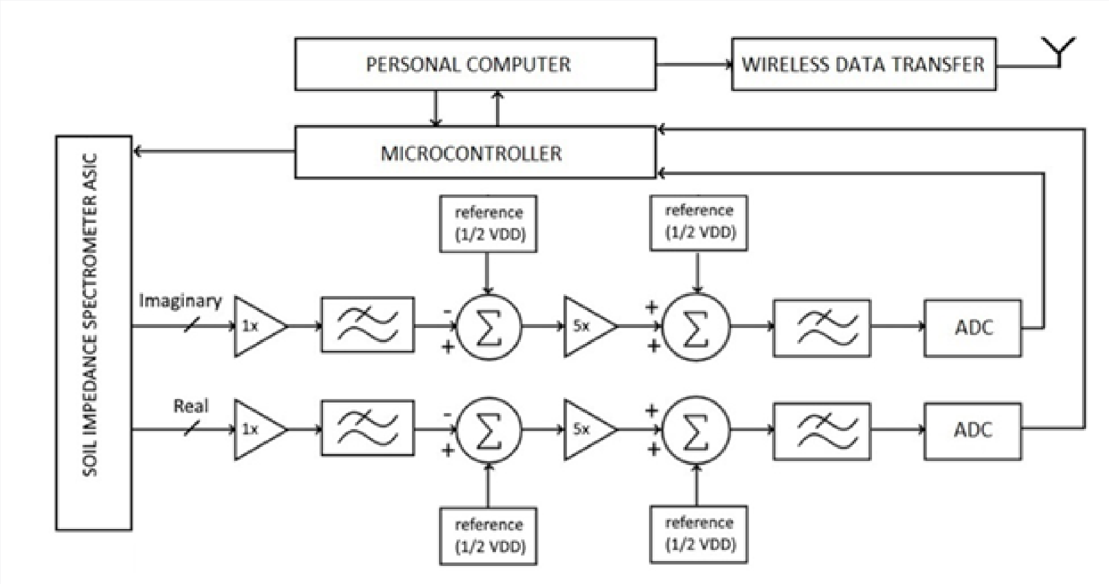


**Figure 5: Simplified schematic of the interface between the soil impedance spectrometer ASIC and the processing unit (PC, notepad, or tablet).**

Data preprocessing is performed to calibrate the obtained imaginary and real parts of soil impedance with the imaginary and real parts of the reference circuit impedance. This procedure is necessary to ensure accurate data acquisition. The reference circuit signals for the final sensor design are measured only once and used to correct other signals acquired with this sensor. We use the corrected signals corresponding to the soil samples to calculate the impedance magnitude and impedance phase. A training set for machine learning is formed from the research dataset measurements corresponding to soil with known chemical properties of phosphorus, potassium and magnesium. The research dataset consists of impedance strengths and impedance phases corresponding to a soil sample. The chemical analysis of soil sample properties performed at KIS includes nutrient values for phosphorus, potassium and magnesium. Tables 2&3 and Figure 6 show the principles of soil sample code formation. Following the fertilizer planning recommendations, the A-E classification was used for each soil component (e.g., phosphorus, potassium, and magnesium). These classification components are then combined to form a XXX code for classifying and predicting the soil properties under test.


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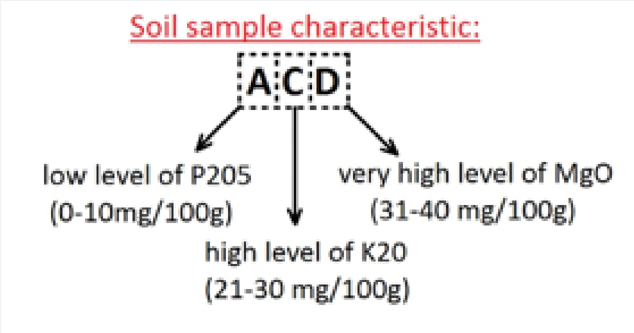


**Figure 6:** Visual description of the soil properties triplet code for soil sample.

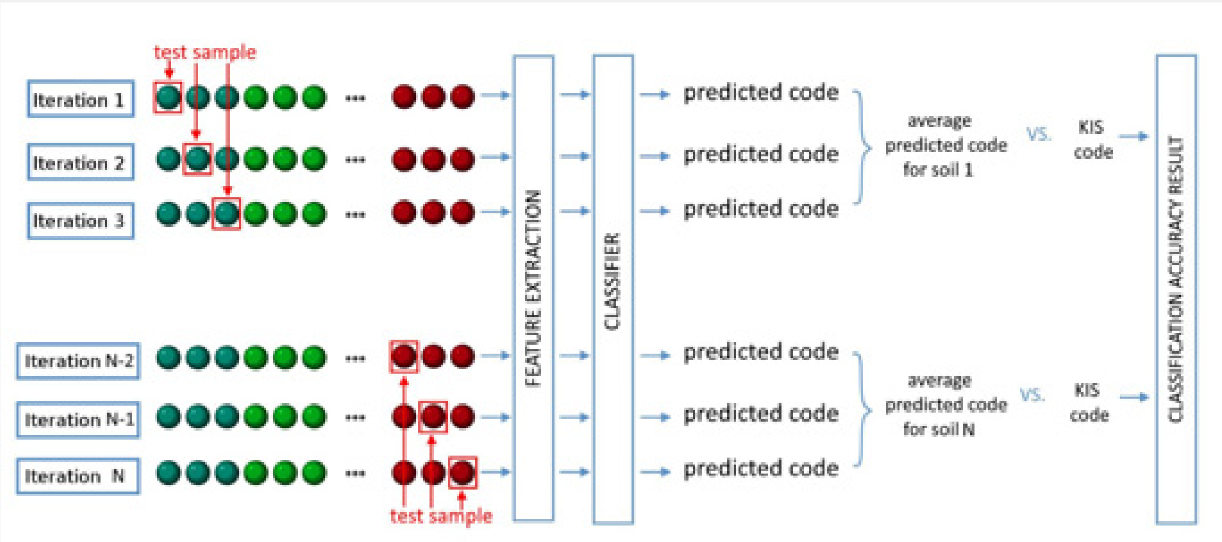


**Figure 7:** The graphic presentation of classification accuracy calculation.

**Table 2:** Triplet KIS code representation (XXX-code in Table 3) for soil chemical properties description.

| | Phosphorus | Potassium | Magnesium |
|---|---|---|---|
| | mg/100g | mg/100g | mg/100g |
| A | <10 | <10 | <10 |
| B | >10 | <20 | 10<B<20 |
| C | >20 | <30 | 20<C<30 |
| D | >30 | <40 | D |
| E | >40 | >40 | >40 |

**Table 3:** An example of the soil samples with codes used in this research.

| lab- name | Phosphorus | Potassium | Magnesium | Phosphorus Level | Potassium Level | Magnesium Level | Triplet KIS code |
|---|---|---|---|---|---|---|---|
| | mg/100g | mg/100g | mg/100g | | | | |
| Sample 1 | 3.4 | 6.4 | 23 | A | A | C | AAC |
| Sample 2 | 3.9 | 6.4 | 23 | A | A | C | AAC |
| Sample 3 | 14 | 6.4 | 24 | B | A | C | BAC |


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| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Sample 5 | 35 | 8.2 | 24 | D | A | C | DAC |
| Sample 6 | 4.2 | 44 | 23 | A | E | C | AEC |
| Sample 7 | 39 | 47 | 23 | D | E | C | DEC |
| Sample 8 | 7.8 | 14 | 22 | A | B | C | ABC |

The training process includes the feature selection procedure [5] and classification using the so-called "classifier". Many classifiers have been proposed in the literature that performs classification with different degrees of accuracy. A comparative analysis was performed to select the classifier with the best results (i.e., the best match between the predicted nutrient content and the actual nutrient content determined at the KIS). The classification accuracy was validated using the leave-one-out method [6]. Only soil samples with known chemical properties were used in this validation (i.e., training set). Three subsamples represent each soil sample to allow more accurate analysis. First, a soil subsample corresponding to the measurement from the research dataset was used as a test sample, while the others were used for machine learning (i.e., training set). Then, the obtained prediction is compared with the actual soil properties (i.e., KIS code). This procedure is performed for all data from the research dataset. The results obtained for three subsamples of the same soil are averaged and used to calculate the overall classification accuracy. In other words, the percentage of predicted characteristics that match the certified laboratory characteristics is used to characterize classification accuracy. Taking three or more measurements of the same soil sample is typical in agricultural informatics to obtain a more accurate and representative result. The procedure for calculating the classification accuracy is shown in Figure 7, where the process is illustrated graphically. During the feature extraction procedure, the signal frequencies with the most relevant information for classification are selected separately for impedance magnitudes and impedance phases. Several feature selection methods are described in the literature. The Principle of Component Analysis (PCA) is selected here as one of the most common and useful [7]. An example of the classification accuracy obtained when the feature selection procedure was used and when the feature selection was not used can be seen in Table IV. It shows a significant performance improvement of the classifiers with feature selection even in the problematic soil sample without using the pre-selection feature introduced in the proposed novel classifier. Figure 8 shows the estimated weights for impedance variables according to the research dataset. The threshold value Th=0.2 is used to reduce features with a small impact on classification accuracy. Thus, 13 features were extracted. Table V shows the frequencies and their indexes obtained during feature selection. The obtained frequencies are then used for both machine learning and test signal properties prediction. Tree Bagger [8] was selected as the most promising classifier. Tree Bagger chooses a random subset of predictors for each decision partition as in the random forest algorithm. The outputs of the classifier are model parameters that are unique to each research dataset. These parameters are estimated once and then used to predict the chemical properties of the soil under study. Table VI shows the classifiers selected for comparative analysis in this research.

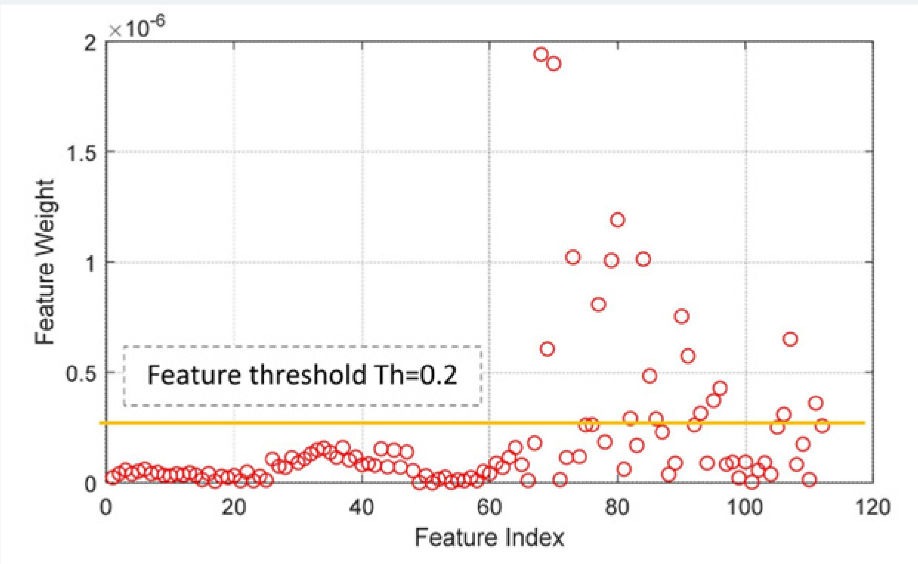


**Figure 8:** Feature index weight for a training set of impedance magnitudes.


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## Results

**Table 4:** Classification performance of the research dataset with the feature selection and without the feature selection.

| | Phosphorus | Potassium | Magnesium |
|---|---|---|---|
| TreeBagger (5), no feature selection | 33% | 48% | 100% |
| TreeBagger (5), With feature selection | 52% | 765 | 100% |

**Table 5:** Indexes of the frequencies obtained during feature selection for soil classification using impedance magnitudes.

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Index | 68 | 69 | 70 | 73 | 77 | 79 | 80 | 84 | 85 | 90 | 91 | 96 | 107 |
| MHz | 1.48 | 1.56 | 1.58 | 1.78 | 2.24 | 2.59 | 2.6275 | 3.16 | 3.275 | 4.0775 | 4.48 | 5.92 | 11.192 |

Table 4 shows the results of the prediction accuracy of the soil sample codes for the research dataset consisting of 21 soil samples collected from different locations in Slovenia with different textures and chemical properties. The feature selection procedure for this dataset estimated five frequencies with weighting parameters greater than Th=0.2. We can see different classification accuracies between the results, with Tree Bagger and Fitcecoc showing the best performance. The least accurate result was obtained using the k- Nearest Neighbor method (i.e., Fitknn). These results are quite acceptable as they have an accuracy of almost 90%. Knowing that the soil sample does not have representative nutrient contents, we can rely on the reasonable assumption that the fertilization schedule is calculated at many points in the studied field since the soil classification is extremely fast. Consequently, the field is mapped in terms of nutrients with a grid sufficient to determine a reliable average fertilizer rate and the proper mix to improve fertility near optimum.

**Table 6:** The Matlab classifiers under analysis.

| | |
|---|---|
| TreeBagger(50, dataset) | Decision Tree |
| TreeBagger(5, dataset) | Regression Decision Tree |
| Fitctree(dataset) | Binary Decision Tree for multiclass classification |
| Classification Tree. fit(dataset) | Classification tree |
| Fitcecoc(dataset) | multiclass models for support vector machines |
| Fitcnb('dataset', 'Distribution', 'Kernel') | multiclass naïve Byes model |
| Fitcknn(dataset) | K-Nearest Neighbour |

**Table 7:** The research dataset classification results using different classifiers with PCA-based feature extraction for soil samples collected in several Slovenia locations.

| Prediction accuracy of the soil sample codes | 1-class tolerance | | |
|---|---|---|---|
| | P | K | M |
| TreeBagger(50 )with feature selection | 86% | 90% | 86% |
| TreeBagger(5)with feature selection | 90% | 86% | 86% |
| Fictree(dataset) with feature selection | 62% | 76% | 67% |
| Classification Tree.fit(dataset) with feature selection | 62% | 76% | 67% |
| Fitcecoc with feature selection | 62% | 67% | 71% |
| Fitcnb with feature selection | 52% | 67% | 81% |
| Fitknn with feature selection | 48% | 71% | 81% |

## Discussion

The goal of the presented study was to develop an optimized classification algorithm and a portable classifier that can predict the content of nutrients in the soil in a short time. Mapping the soil's nutrient content on a particular plot is no longer an expensive and time-consuming affair with this device. The fertilization schedule can be automated with a Global Positioning System (GPS) controlled metering device on the farm tractor. The described soil prediction was tested on five different farms on three plots. The analysis was carried out twice a year under different weather conditions and soil moisture. The test sites were selected to represent the diversity of the Slovenian landscape. The first selected farm was located in the NW (North-West) of Slovenia. The soil there is not very fertile, but it was managed for growing seasonal vegetables with a well thought out crop rotation. The second farm is located in SE (South-East) of Slovenia. The soil


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there is poor and neglected, very muddy and difficult to analyze. The location of the third farm is on the eastern border of Slovenia. The crop there is grown in large plastic tents with automatic irrigation and ventilation. The fourth farm is located in the eastern part of Slovenia. The analysis was carried out on three different vineyards. The soils were clay type and challenging to analyze. The additional feature of the algorithm helped to overcome this and provided the correct prediction. A very similar problem was found in a vineyard in the central-eastern part of Slovenia. Again, the new prediction algorithm proved to be correct.

## Conclusion

This paper describes an improved method for determining the electrical impedance spectrum of soil that provides a reliable, robust, and cost-effective tool for characterizing the soil fertility of an agricultural field and for developing an optimal fertilization plan. This project's result is a portable device for analyzing the soil's electrical impedance spectrum and characterizing it based on the spectrum data. The system is battery powered. It also allows for direct wireless data transmission. The results were verified in several farms with different soil types. An acceptable probability of correct soil class prediction was achieved. Since the prediction algorithm is based on the principle of self-learning, the probability of correct prediction increases with the growth of the learning data set. We believe that the sophisticated methods described in [9] are not required to achieve such results.

## Acknowledgments

The Slovenian Research Agency (ARRS) and the Ministry of Agriculture, Forestry and Food (MKGP) partially funded the project. The author thanks Olga Chambers, Ph.D., for her assistance with the measurements.

## Conflict of Interest

The author declares that there is no conflict of interest.

## References

1. Burton L, Jayachandran K, Bhansali S (2020) The "Real-Time" Revolution for In situ Soil Nutrient Sensing, Journal of The Electrochemical Society, 167(3).
2. Sirsat MS, Cernadas E, Fernandez-Delgado M, Khan R (2017) Classification of Agricultural Soil Parameters in India. Computers and Electronics in Agriculture 135: 269-279.
3. Bodake K, Ghate R, Doshi H, Jadhav P, Tarle B (2018) Soil based Fertilizer Recommendation System using Internet of Things. MVP Journal of Engineering Sciences 1(1):13-19.
4. Chambers, O., Trontelj, J., Tasic, J., and Trontelj ml. J. (2019). New approach to optimization of crop production and environment protection. *Sensors & transducers*, *237*, 159-164.
5. Morgan D, Scofield C (1991) Signal Processing and Feature Extraction. Neural Networks and Speech Processing 130: 163-201.
6. Hastie T, Tibshirani R, Friedman J (2009) The elements of statistical learning (2nd edn.), Springer.
7. Identifying Significant Features and Classifying Protein Profiles- MATLAB & Simulink- MathWorks Switzerland. Ch.mathworks.com. (2020).
8. Create bag of decision trees -MATLAB- MathWorks Switzerland (2020). Ch.mathworks.com.
9. Suchithra M, Pai M (2020) Improving the prediction accuracy of soil nutrient classification by optimizing extreme learning machine parameters. Information Processing In Agriculture 7(1): 72-82.