A Pre-study for the Integration of Edge AI in Plant Science

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Abstract: The use of digital sensors is established in plant science. Multiple aspects of the plant's status or behavior under stress conditions can be described or imaged. Mostly coupled with AI algorithms these devices describe a powerful combination to quantify changes of the plants due to stress conditions for single time points or in time course. The latest developments show the integration of AI routines into sensors, allowing them to measure not only a vast amount of data but also semantic data. This study introduces a state-of-the-art spectral sensing prototype that is tailored to this edgeAI workflow. A first experiment using it as a standalone sensor with an external analysis routine shows the big potential of the later all-in-one measurement routine. In addition, an outlook is given for future challenges that stand between a fast implementation of these devices into practical work routines.

1 Introduction

Nowadays, spectral sensors are an established tool in plant science used to measure plant response to diverse aspects of environmental changes. Especially for the detection of biotic stress, such as infection of fungi or viruses, digital devices have shown their applicability. Although these measurements are available, their applicability in daily work life has to be developed.
The use of spectral sensing in practical scenarios involves the following platform requirements: handling under field conditions, easy usability without deeper technical understanding, affordability as well as a combination with market-available software to cover the whole process from data acquisition, stitching, combination, referencing and transfer to parameter extraction. Nevertheless, the most critical part is the analysis using state-of-the-art tools for knowledge extraction (PAULUS & MAHLEIN 2020). Machine learning models add semantics to the data and enable quantification or at least to determine disease intensity. This includes expressing epidemiology terms of disease severity and incidence with high precision.
The application of digital tools is a key driver for the acceleration of usually manual procedures and work tasks in plant breeding, and crop protection scenarios as well as for an integration into disease forecast systems (ZHANG et al. 2020). Moreover, the use of non-imaging could be a fundamental support to increase productivity, profitability, and early predictability of operational decisions and outcomes in modern farming practices. This study aims to show a use case for spectral sensing and to give insights into future challenges of broad integration into toolchains in plant science and agriculture.
The present study will focus on the introduction of this use case showing the workflow of spectral sensing in agriculture. This approach will show the introduction of a new market available, non-imaging sensor, measuring sixteen different wavelengths and its application for a standard use-case in agriculture / at an agricultural field. The approach includes the detection of a typical virus disease in sugar beet. The shown results combine the use of a market-available hand-held spectrometer with the latest machine learning as an approach for the identification

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of plant diseases. The presented results depict the preliminary stage for a later integration of the AI model into the spectrometer. The use-case aims at a fast and highly automated data acquisition followed by an automated data analysis using standardized data pipelines.

2 Use Case EdgeAI in Plant Science

Virus yellows have become more prevalent within the European Union as neonicotinoids have been banned as seed treatment. Neonicotinoids were an important tool for controlling aphids as virus vectors in the field. This led to an increase in yellowing viruses in sugar beet fields. Dominant virus types in sugar beet are Beet yellows (BYV), beet chlorosis (BChV), and beet mild yellows virus (BMYV). Detection of a single virus infection has already been shown in literature (HOSSAIN et al. 2022). Nevertheless, on practical field sites, multiple infections and combinations with other aspects of stress like drought stress often occur. Facing this, the first step is the ability to differentiate multiple (virus) diseases on the field.
Therefore, a handheld spectral sensor was used. This prototype is almost market available and can be depicted as low cost (< 1000€). It measures within the spectral area of 980 to 1620 nm using 16 bands. The data was acquired at a field trial at the Institute of Sugar Beet Research near Göttingen (Germany). To estimate the spread of virus diseases in sugar beet, the spectrum of BMYV, BChV, and BYV was compared with each other and healthy control. Virus types that are widespread in Germany have been chosen. These types adversely impact beet quality and development and lead to significant yield losses (HOSSAIN et al. 2021).
During the field trial, three blocks were set up, each one for a different virus, along with a control group. Buffer zones were established between the plots to prevent mixed measurements resulting from virus spread through aphids. The virus block was further divided into 6×4 plots. Inoculation began early with more severe symptoms and ended late with light to no visible signs of infection. The plants were inoculated using viruliferous wingless Myzus persicae.
A total of 60 leaves were sampled per treatment for each virus from the plots. The spectrometer (combined with the leaf clip) was used to measure the samples, which were then relayed to a laptop via Bluetooth. It is recommended to use an energy source for the laptop during field measurements over a long period. To ensure high data integrity and avoid measurement errors, a barium sulfate plate was used for calibration, which was repeated every 10 minutes.
The study utilized three machine learning techniques, namely support vector machine (linear), support vector machine (radial), and random forest. These methods were chosen to determine the differences in the data and to predict the accuracy of virus differentiation and classification compared to the control. Results showed that the linear support vector machine outperformed the other two methods in most of the testing combinations. Therefore, further analysis employed this method, and a tuning step was added. The classifier was evaluated to determine the highest accuracy for every cross-validated performance.
The research findings indicate a distinct difference between the virus species and the control plants. The inoculation readings were taken 50 days post-inoculation (50 dpi). The accuracy of the linear classification ranged from 0.82 to 0.96 as shown in Fig. 1.

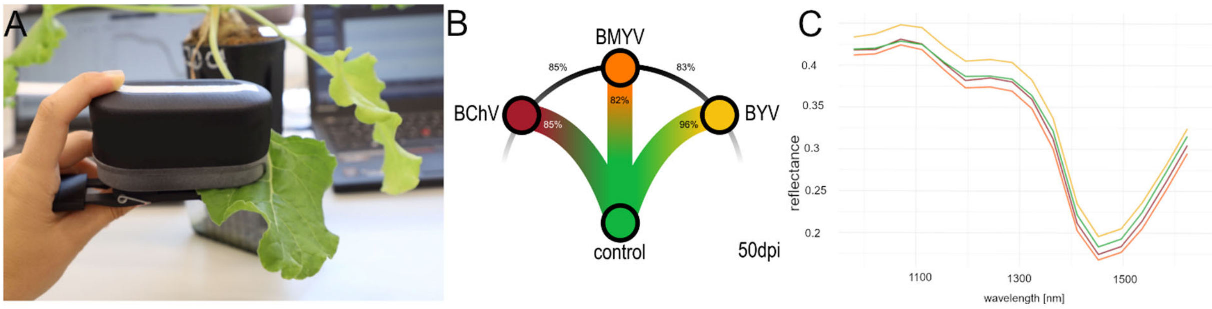

Fig. 1: A new spectral sensor prototype is used to measure sugar beet plants using a leaf clip (A). With this sugar beet leaves were measured including a healthy control group and three different inoculated virus types (beet virus yellows virus BYV, beet chlorosis virus BChV, and beet mild yellows virus BMYV). The sensor measurements can be used as input for a machine learning routine that can perform a differentiation between the three different virus types and the healthy control group (B). It was possible to reach accuracies between 83-96 % accuracy for differentiation of two groups using a 2-class classification. All machine learning models are based on a spectral signature of sixteen bands between 1000-1600nm (C)

3 A view to the future

The experiment's results indicate that the integration of AI on sensors has a high level of usability and a broad range of applications in plant science and agriculture. Rising challenges for the integration of these new digital technologies into practical agriculture can be separated into at least three different groups. Technical aspects, social aspects as well as practical aspects (see Figure 2).

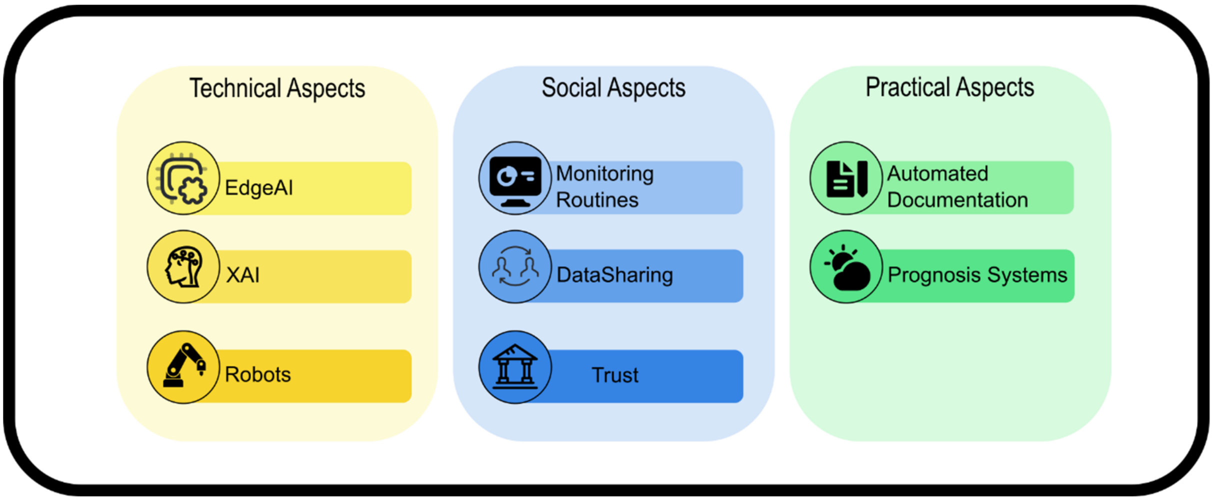

Figure 2: Challenges for the introduction of spectral sensing in the future can be grouped into technical aspects, social aspects, and practical aspects. While technical aspects cover the combination of AI and sensing (edgeAI), the explainability of machine learning (XAI), and the use of robots, social aspects cover the trust in AI, technology, and monitoring routines. As an acceleration in AI use in daily routines is a question of data availability data sharing becomes very important. Practical issues tackle the integration into automated documentation routines and the efficient use of prognosis systems for planning agricultural tasks like fungicide application.

One of the future's technical challenges is integrating machine learning routines into EdgeAI sensors, which is not simply copying a model. This will transform the routine of image collecting to the collection of information as semantics is extracted from the images. Mostly integrated

on moving platforms like drones or robots, these sensors can provide substantial value. Nevertheless, improving autonomy and navigation skills, the generation of high-precision maps, and learning to fulfill agricultural tasks as shown today by weeding robots depicts another challenge. Automation of tasks by robots without human interaction and even without the possibility of intervention is demanding and needs sophisticated machine concepts.
Even in automation machine learning is an essential and critical part. These models are a black box and the way how a classification or regression result is reached is not visible. Thus, a further challenge is the explainability of AI models (XAI).
All this leads to social aspects of future challenges. Trust in robots and machine learning models is essential. Here XAI and practical evaluation scenarios are the basis. Here intense work and concepts for test environments and field trials are needed. As AI models depend on heterogeneous and high-quality training data concepts of data sharing are key (PAULUS & LEIDING 2023). An improved quality by international, cross-disciplinary, and cross-application data collection and sharing leads to higher quality in AI models. Nevertheless, therefore aspects of data copying and property claims have to be solved. Finally, the establishment of monitoring routines needs a specific social trust and its value has to be committed to the society. Not just drones and robots, but also the value of their services need to be visible.
There are also practical aspects. As farmers need to calculate the direct effort and its profitability digital tools need to fulfill this aspect first. The first task can be the automated documentation to comply with the law and regional regulations. Coupled with tractor information systems for machine control or farm management systems most application and management procedures are known and need to be collected, aggregated, and interpreted. For the plant cultivation part more precise forecast of weather, yield, but also market prices coupled with monitoring results from the field by drones and robots can bring substantial effort.

4 Conclusion

A study was conducted to test the effectiveness of a manual spectral measurement device in identifying virus types in sugar beet. The results showed that the device was successful in accurately differentiating between various virus-infected plant leaves, with a high accuracy rate of over 90%. This device is considered a first step towards the integration of AI, specifically edgeAI, into farming practices. However, further research is needed to address the challenges that may arise in its adoption and implementation into the daily routines of farmers. The study provides a detailed examination of these challenges.

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6 Literature

HOSSAIN, R., ISPIZUA YAMATI, F. R., BARRETO, A., SAVIAN, F., VARRELMANN, M., MAHLEIN, A.-K. & PAULUS, S., 2022: Elucidation of turnip yellows virus (TuYV) spectral reflectance pattern in Nicotiana benthamiana by non-imaging sensor technology. Journal of Plant Diseases and Protection, **130**(1), 35-43, https://doi.org/10.1007/s41348-022-00682-9.

HOSSAIN, R., MENZEL, W., LACHMANN, C. & VARRELMANN, M., 2021: New insights into virus yellows distribution in Europe and effects of beet yellows virus, beet mild yellowing virus, and beet chlorosis virus on sugar beet yield following field inoculation. Plant Pathology, **70**(3), 584-593, https://doi.org/10.1111/ppa.13306.

PAULUS, S. & LEIDING, B., 2023: Can Distributed Ledgers Help to Overcome the Need of Labeled Data for Agricultural Machine Learning Tasks? Plant Phenomics, **5**, https://doi.org/10.34133/plantphenomics.0070.

PAULUS, S. & MAHLEIN, A.-K., 2020: Technical workflows for hyperspectral plant image assessment and processing on the greenhouse and laboratory scale. GigaScience, **9**(8), https://doi.org/10.1093/gigascience/giaa090.

ZHANG, X., CAO, Z. & DONG, W., 2020: Overview of Edge Computing in the Agricultural Internet of Things: Key Technologies, Applications, Challenges. IEEE Access, **8**, 141748-141761, https://doi.org/10.1109/access.2020.3013005.