RISCE- AN EXPLAINABLE ML CHAIN FOR PRACTICAL SUSTAINABLE AGRICULTURE

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ABSTRACT

Knowledge systems in sustainable agriculture see a big gap with end users due to lack of easy-to-use interfaces with existing knowledge. Adding to the problem, decisions coming from black-box models are not understandable for most users. We try to bridge the gap with an integrated chain of explainable ML models to address the most useful applications in the agri-food industry. To make the integrated model available to users and help them draw benefits out of it, we also propose a novel idea of an explainable ML framework for interaction with human users. This human-in-the-loop approach makes ML models more trustworthy. End-users understand the output from ML models and also improve models with feedback. The application interface is also proposed to have features for multilingual communication among users to build communities. Feedback from communities help further refine ML models. The proposed system is named as Reusable Intelligent solution for Cultivation Enhancement (RISCE).In this article, we provide a demonstration of our system with an intrinsically explainable model for crop vigor analysis.

***Index Terms*—** Sustainable agriculture, Explainable Machine Learning (xML), Agri-food industry, Knowledge gap, Human-in-the-loop

1. INTRODUCTION

A gigantic amount of successful research work has been done in the field of precision agriculture with remote sensing data and machine and deep learning. Still, we observe a big gap between end-users (e.g., agricultural stakeholders unaware of intricate science and technologies) and the benefits of those researches. The problem originates from a lack of tools at the end of the users and a lack of explainability, or in other words, "black-boxedness" at the end of the models. This problem has more intricate effect than it may sound as it means to have wasted research efforts and unaddressed knowledge requirement. This leads poor land and soil management, wastage and suboptimal production which in essence, affects sustainability of the environmental resources (see Fig.2).

The problem sees different faces across the globe. In the developing countries, it is a lack of tools, cultural gap and lack of education among farmers while in the developed countries it is more often caused by unverifiability of information and lack of trust [1]. Rust et. al surveyed farmers in two countries in Europe and found a lack of trust on traditional experts. Farmers rather reply on information found in the internet or prefer to ask another farmer
while major decisions that affect global sustainability. To address this issue, we propose a framework for trustworthy agricultural models to gain confidence of the end-users. We surveyed more than 100 famers in the east and north regions of India and found that Model-based farming decisions have promising future. However, this can be mainstreamed by involving farmers into the decision process.
In this paper, we present a state of the art of recent models in precision agriculture, comment of the black-boxedness of the models, and propose solutions to transform them into explainable models and make them trustworthy by involving human users. An initial challenge in this approach may be the diversified approach in research, which indicates there would be no 'one size fits all' explainability technique that we can follow. However, we choose to attempt "white-boxing" the best research approaches to make them more applicable in the practice of sustainable agriculture.

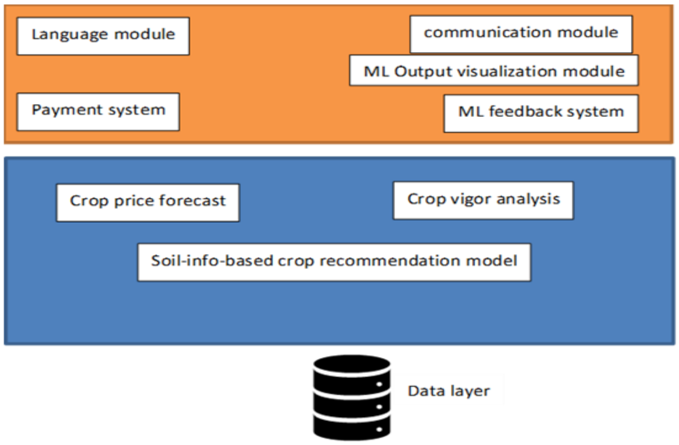

Fig. 1. RISCE Schematic diagram

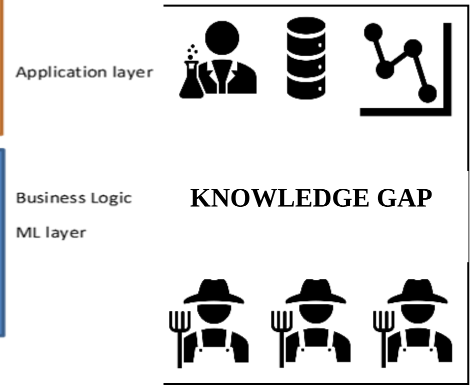

Fig.2. knowledge gap between end-users and scientific studies

2. CHOSEN AGRI-ML MODELS IN GEOSCIENCE AND REMOTE SENSING: OUR CANDIDATES FOR WHITE BOXING

In this section we list some practical and promising ML researchers in the field of sustainable agriculture and their explainability properties as stated by Roscher et.al [2]. A model can be called explainable when:

i. it is transparent in the algorithm (i.e the algorithm can be presented as a mathematical formula), model input out relation and design choices;
ii. Generate interpretable outcomes with variables intermediate layers,
iii. Gives scientifically verifiable outcomes and,
iv. Integrates sufficient amount of domain knowledge

In this article, we have chosen to concentrate on of one of three applications in precision agriculture, and research on the best approaches therein (See Table 1). In the RISCE project, we focus on crop price forecast, crop vigor analysis and soil-info-based crop recommendation model. Peng et. al. proposed a price forecast model is developed with open data in Taiwan market using Auto-regressive model and Artificial neural networks (ANN) in [3]. The layers used in ANN can be better explained although does not seem necessary as the approach is altogether explained using response surface methodology. We rather focus on creating visual interpretations for end-users and train the model with new data. Another price forecast model for horticulture data is proposed by [4]. The authors have used ARIMA and a recurrent neural network model for price forecast. Deep RNN network is usually considered black-box and researchers have used four methods, namely, ablation, permutation, added noise, and integrated gradients [5].

A crop recommendation model based on previous years' experience from farmers is proposed in [6] using data mining and ensemble methods. The approach already involves human interaction and therefore, is rather white-box. The performance is enhanced using k means clustering, which is already a transparent algorithm [1]. We can test the usability of this method in our particular use case of crop vigor analysis with an intrinsically explainable model. This improves the explainability of the work proposed by Kerkech et. al[7].

As an initial experiment, we plotted statistics based on the NDVI values from drone and Sentinel-2 pixels from a case study of Vineyards in Spain. The drone images have a resolution of 0.13m whereas Sentinel-2 images have a resolution of 10m. Applying zonal statistics reveals that there are varying numbers of drone pixels in the Sentinel-2 NDVI zones depending on the study area. We computed some statistics based on these drone pixels. The NDVI value obtained in the drone pixels were grouped to provide meaning insights.

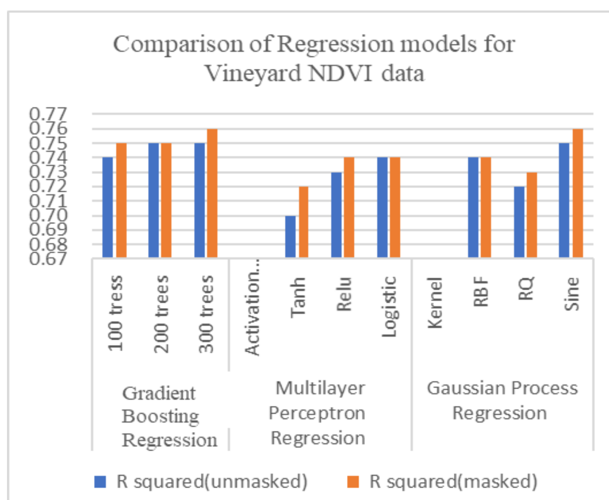

Fig. 3. Regression models for crop vigor analysis

In the first plot, we plotted the lowest values found in every Sentinel-2 NDVI zone. We rounded off the zonal NDVI values which gets us more than one lowest value in the zones. We see that the low NDVI zones in Pradorey (see first plot, Fig. 2) have greater variance in the data; this is because there are various zones having low NDVI values in the Sentinel-2 image, each with corresponding lowest NDVI observed in the drone pixels.

We see that the lowest values drone pixels in lower value NDVI regions have a wider range, but in any case, the highest values are stabilizing. The next plot shows the status of mean value computed at various Sentinel-2 NDVI zones. Next, we plotted the lowest NDVI values in soil-segmented drone pixel for the NDVI zones are plotted. The last plot in Fig. 2 shows the mean of NDVI values in soil-segmented drone pixels at various Sentinel-2 NDVI zones. We see a similar behavior as in the second plot for unsegmented drone pixel, except that the lowest values in the drone pixels is higher (0.3) and the plot looks less steep in plot 4 than in plot 2. This can be explained by the removal of soil-pixels which contributed to low NDVI values in the 2nd plot, thus giving a wider spectrum of values in the Sentinel-2 zones.

After visually exploring the statistical relationship between the values from low resolution and high-resolution images, we trained a regression-based machine learning model to correctly capture this behavior. The results were further grouped to provide on single NDVI mean value from the drone pixels in each Sentinel-2 NDVI zone as shown in Fig. 3. Thus, we produced training data for both kinds of drone images, soil-pixel segmented and unsegmented. In both the cases, we saw similar behavior, with the natural exception that the lowest NDVI value lies higher in case of soil-segmented pixels. Three regression models (see Fig. 3) were trained for the soil-segmented and soil-unsegmented cases, among which, an ensemble method called boosted regression trees gave the highest R^2 value. Some experiments with training sample size and test sample size reveal the best train and test sample sizes as given in Table 1.Fig. 4 shows the linear regression graph predicting rectified NDVI values from Sentinel-2 images. This graph is an example with a GPR model trained on unsegmented drone pixels.

VALIDATION

To validate the idea in the case study, we run a clustering on the NDVI maps and plot the unrefined NDVI cluster map and the refined NDVI cluster map. We can see that the refined map is actually closer to the ground truth (see appendix).

Table 1. state of the art methods and explainability work

Research paper	Explainability	Our target
Crop Price Forecast Model [4]	White-box model	Create visualizations for end-users(farmers)
Crop Price Forecast Model [5]	Black-box model	Create explanations and visual interpretations
Crop Vigor Analysis [7]	Black Box	Do similar analysis with inherently explainable models

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